Attentiveness modulates reaction-time variability

findings from a population-based sample of 1032 children

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Abstract

Children's cognitive performance varies from moment-to-moment in a way that is shaped by, and in turns shapes, their development. What drives this variation remains poorly understood. One field where within-person variability in cognitive performance has seen unprecedented interest, may hold some answers. For a large proportion of children with Attention/Deficit Hyperactivity disorder, high within-person variability in reaction times is considered a key cognitive characteristic. This finding is accompanied by a rich theoretical literature that offers empirically testable predictions. However, reliance on suboptimal methods and datasets has obstructed insight from empirical tests. We identify three compounding sources of heterogeneity that reside in: statistical estimation, cognitive tasks, and psychopathology measurement. We address this heterogeneity to revisit pertinent theoretical questions. First, we isolate a theoretically motivated estimate of reaction-time variability from often confounded cognitive characteristics, using dynamic structural equation modeling. We use this estimate of reaction-time variability to test the specificity of its association with Attention/Deficit Hyperactivity disorder, over-and-above other developmental problems in a population-based cohort of 1032 children aged 5.5 to 13.5. We find that reaction-time variability is specifically associated with symptom-severity in the inattention domain. Second, we test four hypotheses about mechanisms driving reaction-time variability, and their relation with individual differences in inattention and hyperactivity/impulsivity severity. We use a unique task design in combination with latent difference score models to isolate the effect of distinct mechanisms on reaction-time variability. Our findings support changes in attentiveness as a mechanism driving reaction-time variability. We show how a close dialogue between neuroscience, clinical psychology, and psychometrics can accelerate our understanding of within-person variability in cognitive performance.

Keywords: reaction-time variability; intraindividual variability; development; ADHD; dynamic structural equation modeling

Introduction

Children's cognitive performance waxes and wanes along with the dynamic patterns exhibited by their endogenous environment and external perturbations. This pattern of rapid, relatively reversible, changes in cognitive performance is termed *intraindividual variability* and was historically considered noise (Nesselroade, 1991; Fiske and Rice, 1955; Cattell et al., 1947; Woodrow, 1932). Multiple theoretical frameworks have pushed back against the suggestion that variability is mere noise, by proposing that the inherent inconsistency in human behavior reflects substantively meaningful processes that vary across children and are both cause and consequence of developmental differences (Gottlieb, 2007; Nesselroade, 1991; Ford and Lerner, 1992, Hull, 1951). Within studies of early development, this theoretical premise has been empirically corroborated by the ubiquitous finding that a substantial proportion of children diagnosed with Attention-Deficit/Hyperactivity Disorder (ADHD) show elevated variability in reaction-times during cognitive testing (Kofler et al., 2013; Karalunas et al., 2014; Castellanos and Tannock, 2002; Leth-Steensen et al., 2000). This robust association naturally led to a more ambitious search for the mechanisms driving reaction-time variability. Today, reaction-time variability is considered one of the best cognitive correlates of ADHD and an etiologically relevant correlate of the disorder (Hauser et al., 2016; Kofler et al., 2013). As such, this literature-base offers fertile conceptual ground to tease apart the underlying mechanisms affecting differences in intraindividual variability. However, reliance on suboptimal methods and datasets has slowed down progress, leading to substantial heterogeneity in the processes that reflect reaction-time variability, within and across studies, making it difficult to identify its mechanisms. In this paper, we will introduce and apply innovations from relevant scientific fields in conjunction with a unique task design, to bolster our understanding of the mapping between ADHD, reaction-time variability, and its candidate mechanisms.

Heterogeneity within traditional estimates of reaction-time variability

To reliably map mechanisms to reaction-time variability we need to ensure that we are isolating the construct of interest (variability) using suitable measures. Most substantive interpretations of reaction-time variability within the ADHD literature converge on the conclusion that variability is composed of *randomly occurring inordinately slow trials* (Kofler et al., 2013; Geurts et al., 2008; Karalunas et al., 2013; Karalunas et al., 2014; van Belle et al., 2015). However, classical approaches such as the intraindividual standard deviation (i.e. the deviation of reaction-time at each trial from a person's mean reaction-time, $ISD_i = \sqrt{\sum \frac{(y_{i,t}-y_i)^2}{T_i}}$) and the intraindividual coefficient of variation (the iSD divided by a person's observed mean score, $ICV_i = \frac{iSD_i}{y_i}$) do not isolate variability in the way this definition demands. Instead they conflate the effects of multiple processes within a cognitive time-series leading to biased estimates and suboptimal inferences. For instance, it has been shown that systematic changes in time-series data, in the form of trends, greatly inflate variability estimates (Wang et al., 2012). This means that a child who steadily improves, or worsens, without short-term fluctuations around that trend may be mistook for a child who demonstrates high variability, clouding our understanding of the construct of interest.

Similarly, more suitable metrics such as parameters from Ex-Gaussian models cannot incorporate information about accuracy and are sensitive to trend effects (e.g. Tarantino et al., 2013), while drift diffusion models have been criticized for only being applicable to binary-choice paradigms (Karalunas et al., 2014). Therefore, if we want to understand the mechanisms and consequences of variability, we must develop and apply models that align with our conceptual assumptions, succeed at quantifying and isolating intraindividual variability as distinct from other phenomena, and are applicable to multiple data structures.

Heterogeneity within cognitive tasks

A compounding source of heterogeneity stems from the multifaceted nature of cognitive tasks and their differential interaction with diverse individuals. The multifactorial nature of cognitive tasks creates an interpretative problem when attempting to probe the active mechanisms that drive characteristics of cognitive performance (Schweizer, 2007), such as variability. When cognitive tasks are viewed as a person-task interaction, it becomes clear that diversity can also arise from subjects (e.g. Rommelse et al., 2015; Anderson, 1992). For instance, Biesmans et al., (2019) showed that amongst lower intellectual ability groups, tasks measuring executive functions may measure basic cognitive processes, such as processing speed, rather than distinct executive functions. This means that tasks may measure different constructs depending on the ability of the population under study, as well as depending on the degree and manner in which processing speed is taken into account (Rommelse et al., 2015; Santegoeds et al., 2022). Therefore, a crucial step towards discovering the mechanisms underlying momentary cognitive fluctuations resides in the design and use of tasks that modulate key cognitive components, thus facilitating insight. These tasks should ideally allow us to separate the influence of candidate mechanisms from other primary and higher-order cognitive processes and measure the same processes across the ability spectrum.

Present study

We aim to remedy these two challenges by combining a unique study design with psychometric innovations. First and foremost, we introduce a novel statistical framework that allows us to isolate a distinct component of reaction-time variability from other aspects of cognitive performance (Figure 1). This framework is dynamic structural equation modeling (DSEM; Asparouhov et al., 2018), which unifies innovations in time-series modeling, structural equation modeling, and multilevel modeling to open new possibilities for inquiry into individual differences in within-person variability.. Second, we use these tools in performance measures of a population-based sample of children aged 5-13 years (n = 1032). A self-paced cognitive task was administered in which the required cognitive demands (e.g., interference control, sustained performance over time) varied across blocks. This design allows us to isolate distinct task demands that are hypothesized to affect (differences in) reaction-time variability, while also taking differences in processing speed into account (Santegoeds et al., 2022). We apply these innovations to revisit questions from the rich theoretical literature on ADHD and its association with reaction-time variability.

Our first research aim is to test the phenotypic (a)specificity of reaction-time variability. We want to know whether reaction-time variability is specifically related to greater

ADHD-symptom severity, or whether it is associated with symptoms across multiple domains of developmental problems, namely emotionality, conduct problems, prosociality, and peer relations. We deem this question pertinent because despite more than 300 studies on the association between reaction-time variability and ADHD, this matter is still unclear (Kofler et al., 2013; Karalunas et al., 2014; Salum et al., 2019). A likely culprit for this uncertainty is the heterogeneity within reaction-time measures that may complicate mapping differences in cognitive fluctuations to differences in specific behavioral profiles. This heterogeneity is further exacerbated by ignoring the possibility that the domains of inattention and hyperactivity/impulsivity are qualitatively distinct (e.g. Willcutt et al., 2012). Lumping these distinct domains into the unitary construct of ADHD in the majority of studies examining its associations with reaction-time variability (278/319 according to Kofler et al., 2013), plausibly adds another layer of heterogeneity. Thus, in a second step, we will increase the granularity of our measures to ask if reaction-time variability is specifically related to individual differences in the severity of inattention symptoms *or* hyperactivity symptoms.

In sum, our first two research questions are meant to address the dual challenge of combining specific symptoms into catch all diagnostic domains and failing to adequately separate variability from other cognitive performance characteristics to more accurately describe the pattern of associations between reaction-time variability and symptoms of developmental problems. To answer our questions, we will apply DSEM to a large cohort of 1032 children aged 5.5 to 13.5 years old who completed a unique battery of cognitive tasks, the COTAPP (Rommelse et al., 2018). Psychopathology assessments will be taken from two continuous teacher-report questionnaires: a measure of multiple domains of psychopathology and a measure that separates ADHD symptoms into two continuous subdomains, inattention and hyperactivity/impulsivity.

Our second research aim is to map mechanisms of reaction-time variability to individual differences in the subdomains of inattention and hyperactivity/impulsivity. This line of inquiry is enabled by the unique task composition of the COTAPP cohort that allows us to use a subtractive method to isolate mechanistic components driving cognitive fluctuations, by assessing differences in reaction-time variability across tasks. In the present paper we will test four mechanistic hypotheses from the ADHD literature using the COTAPP task-battery.

H1: Children with a higher severity of inattention and/or hyperactivity symptoms will show a greater decrease in reaction-time variability after incentivizing speed and accuracy in performance. This hypothesis is a behavioral prediction from the adaptive gain theory, whereby reaction-time variability should decrease under task conditions with high perceived task-utility (Aston-Jones and Cohen, 2005). The adaptive gain theory of locus-coeruleus (LC) function, proposes that LC function can transition between two states: a phasic state and a tonic state (Aston-Jones and Cohen, 2005). Transitions between these two states are modulated by perceived task-utility which is monitored by the orbitofrontal cortex (OFC) and the anterior cingulate cortex (ACC), both of which provide direct inputs to the LC. The phasic state is triggered when perceived task-utility is high. Here phasic norepinephrine (NE) activity to task-stimuli is high and tonic NE activity is low. This leads to exploitative behavior that optimizes responding to task-relevant stimuli and diminishes the response to task-irrelevant stimuli, which manifests as low reaction-time variability. The tonic phase is triggered under low perceived task-utility. The tonic phase corresponds to low phasic responsivity to task-related stimuli and high tonic activation. This leads to exploratory behavior which serves the search for new rewarding stimuli and manifests as high reaction-time variability. We will test our first hypothesis by comparing children's reaction-time variability on a 2-choice reaction time task with a rewarded choice reaction-time task. Our reasoning is that rewarding speed while maintaining accuracy will increase the perceived utility of task-related stimuli, leading to a phasic state and a decrease in reaction-time variability. The degree of difference should be greater in children with a higher severity of inattention and/or hyperactivity symptoms, given that attention disorders are proposedly characterized by predominantly tonic responding (Aston-Jones et al., 1999; Hauser et al., 2016). Conversely, children with lower inattention and/or hyperactivity severity are likely to show a lower increase in exploitative behavior due to ceiling effects (e.g. Liddle et al., 2011).

H2: Children with a higher severity of hyperactivity symptoms, but not necessarily inattention symptoms, will show a greater increase in reaction-time variability following a spatial interference manipulation. This hypothesis stems from the behavioral inhibition deficit model which predicts that children will behave more variably in tasks where they need to inhibit a prepotent/ongoing response to successfully perform (Barkley, 1997). The behavioral inhibition deficit model posits that inhibition deficits are a core aspect of ADHD. This behavioral inhibition deficit is hypothesized to directly, or through its indirect effects on executive functioning, manifest as behavioral variability in reaction-time tasks (Barkley, 1997). To test this hypothesis we will compare the 2-choice reaction time task with the interference choice reaction-time task. Further, within Barkley's framework behavioral inhibition deficits are primarily linked to hyperactivity, while inattention can be seen as a consequence of inhibition difficulties (Barkley, 1997). Barkley makes a qualitative distinction between the type of inattention that arises as a byproduct of inhibition difficulties and the inattention that resides in the inattentive type of ADHD. Therefore, the degree of difference in reaction-time variability between the two tasks should be greater in children with greater hyperactivity severity, but not necessarily inattention severity.

H3: Children with higher inattention and/or hyperactivity severity will show a greater difference in their reaction-time variability following approximately 30 minutes of cognitive testing designed to tax their sustained attention. Attentional lapses are posited as a cause of reaction-time variability across multiple theoretical frameworks (see Kofler et al., 2013 for an overview). Through the lens of the adaptive gain theory, attentional lapses are a byproduct of the highly distractable state that accompanies the extreme bounds of LC activity (Aston-Jones and Cohen, 2005; Unsworth and Robison, 2018). Prior empirical studies have shown that as time-on-task increases people tend to shift to the lower bound of LC activity, i.e. arousal and alertness decreases, leading to an increase in attentional lapses and reaction-time variability (Unsworth and Robison, 2018; 2018; Aston-Jones et al., 1994; Aston-Jones et al., 2007). Children with ADHD have well-documented impairments in sustained attention (e.g. Rommelse et al., 2011 for a review), in fact, studies have shown that their sustained attention declines faster than controls (Huang-Pollock et al., 2006; 2012; Bubnik et al., 2015). Thus, we expect the effect of our manipulation to be more pronounced for children with greater inattention and/or hyperactivity severity. To test this hypothesis we compared the 2-choice reaction-time task to a vigilance choice-reaction time task, that is identical to the 2-choice reaction time task but is presented after approximately 30 minutes of cognitive testing.

H4: Children with higher inattention and/or hyperactivity symptoms will show a greater increase in reaction-time variability following a longer intertrial interval. This hypothesis stems from the cognitive energetic model (CEM) and provides a different explanation for attentional lapses within ADHD, by proposing that state regulation deficits lead to attentional lapses and subsequently behavioral variability (Sergeant, 2004; Kofler et al., 2013). Akin to the adaptive gain theory CEM proposes that deficient arousal regulation underlies variability. However, arousal in the CEM is linked to stimulus encoding and phasic NE release, pulling from earlier work from Pribram and McGuinness, 1975. In contrast Aston-Jones & Cohen's notion of phasic NE release is empirically linked to central decision processing (Karalunas et al., 2014). The CEM posits that children with ADHD have deficient arousal regulation and that this is exacerbated in tasks with longer event rates (i.e. time between trials; Sergeant, 2000). To test this hypothesis we compared the vigilance reaction time task (to control for differences due to sustained attention) with the event rate reaction-time task. According to the CEM, we expect to see a greater degree of difference in reaction-time variability following the event-rate manipulation and this difference will be greater in children with greater inattention and/or hyperactivity severity.

For our last research aim we want to answer a simpler translational question. We want to know which task, within the COTAPP testing battery, produces a reaction-time variability estimate that is most strongly associated with symptom severity in children with inattention or hyperactivity symptoms. These results may serve the pragmatic purpose of informing task selection for future studies.

Methods

1.1 Participants

We analyzed a sample of 1032 children aged 5.5 to 13.5 years who completed the Cognitive Task Application (COTAPP)—a computerized block-wise cognitive testing battery (Rommelse et al., 2018). This is a population representative sample of children in the Netherlands. To achieve country-wide coverage children were selected from twenty-two elementary schools based on postal codes. The ethnicity distribution, based on migration status, is closely related to the distribution in the Dutch population (i.e. positive migration status in-sample 26.1 percent versus 25 percent in the population). The distribution of IQ-scores also closely reflects the IQ-scores in the population (mean = 100.5, SD = 16.2; as measured by the vocabulary and block pattern subsets of the Weschler Intelligence scale, 3rd edition or the Wechsler preschool and primary scale, 3rd edition). This is not the case in 12- to 13-year-old children within our sample, who scored lower than their norm group. There is a weak negative correlation between age-adjusted IQ-scores and age (r = -0.11, p = 0.01). Ethnicity, age, and gender are not associated in our sample.

1.2 Procedure and materials

1.2.1 Neuropsychological assessment

We analyzed six blocks of cognitive tasks included in the COTAPP (Rommelse et al., 2018), as illustrated in Figure 1. Each task is a variation of a choice reaction time task, with manipulations designed to elicit more specific information depending on the manipulation. Tasks are completed by children in the following sequence, with every task starting after a short series of practice trials. First, the simple reaction time task assesses basic information processing speed across 20 trials. The participant is instructed to respond to a target stimulus that appears in the center of the screen, as soon as it appears, using a single response key. Second, the 2-choice reaction time task assesses higher-order information processing speed across 30 trials. The participant needs to press the correct response-button from two options which are tied to a different target stimulus ("yes-button" for X-stimulus and "no-button" for Y-stimulus). The target stimulus appears at the center of the screen. The simple reaction time task and the 2-choice reaction time task differ in terms of cognitive load. Third, the rewarded choice-reaction-time task assesses the effect of algorithmically administered rewards on higher-order processing speed across 40 trials. The task is identical to the 2-choice reaction-time task with the addition of a dynamic tracking algorithm which administers a reward each time a participant exceeds their individual response speed while remaining accurate. The initial individual response speed for each participant is based on their performance in the 2-choice reaction time task. After each rewarded response, the response speed that needs to be exceeded increases, while after each incorrect and/or slow response (in relation to current speed limit) the response speed decreases. By comparing the 2-choice reaction time task and the rewarded choice reaction-time task we can assess the effect of external incentives on a participant's higher-order response speed. Fourth, the interference choice reaction-time task assess interference control across 40 trials. The task is identical to the 2-choice reaction time task, except that the target stimulus does not appear in the center of the screen. Instead, the target stimulus appears either on the right side of the screen, or on the left. If the target stimulus appears in the same direction as the response key that it is tied to, the trial is congruent. Otherwise, the trial is incongruent. Incongruent trials evoke two contrasting responses: one from the stimulus-key association and one from the spatial location (e.g. stimulus X tied to the button on the right side appears on the left side of the screen). Stimulus congruency is evenly split across trials and randomly ordered. Order is constant across participants. Comparing the interference choice reaction-time task with the 2-choice reaction-time task allows us to assess interference control. Fifth, the vigilance choice-reaction-time task assesses sustained attention by using an identical paradigm as the 2-choice reaction-time task over 30 trials. At this point participants have completed an entire test battery and the discrepancy between the vigilance choice-reaction-time task and the 2-choice reaction-time task can be used to assess the effect of taxing children's sustained attention. Sixth, the long inter-trial-interval (ITI) choice-reaction-time task assesses arousal regulation capacity across 20 trials. The inter-trial interval is increased from 450-750ms to 3000-6000ms. The extended inter-trial interval makes it more difficult to maintain arousal. By comparing the vigilance choice-reaction-time task with the event-rate choice-reaction-time task, we can gauge participants' arousal regulation capacity.

1.3 Baseline teacher-report assessment

1.3.1 Behavioral measures

Strengths and Difficulties questionnaire (SDQ). The SDQ is a brief measure of psychopathology and prosocial behavior in four- to 16-year-old youths (Goodman, 1997). In our study, we analyzed the teacher report version of the SDQ. The 25 items of the SDQ are measured on a 3-point Likert scale (Not True, Somewhat True, Certainly True)

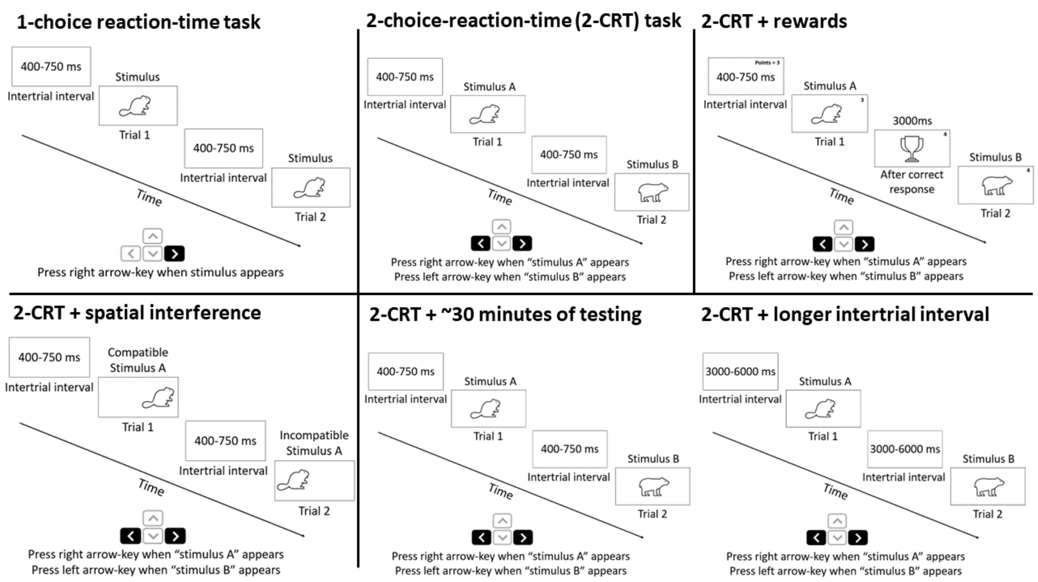

Figure 1. Schematic representation of cognitive tasks used in COTAPP assessment

and divided into five factors: emotional symptoms, conduct problems, ADHD problems, peer problems, and prosocial behavior. The grouping of items is based on factor analyses and current nosology (Goodman, 2001). A recent study on the dimensionality, age- and gender-invariance of the SDQ concluded that for children aged five to 14, a five-factor structure fits well and the factors are gender and longitudinally invariant (Murray et al., 2021). For a systematic review of studies assessing the psychometric properties of the SDQ see Kersten et al., 2016. For the item content of the SDQ see Appendix A in Goodman, 1997. In the present study, we used total scores for each of the five domains (i.e., aggregates of item scores) to represent children's severity of behavioral dysfunction or degree of prosocial behavior within the last six months or the current school year.

Strengths and Weaknesses of ADHD-Symptoms and Normal-Behavior (SWAN) Scale. The SWAN scale (Swanson et al., 2001) is based on the 18 ADHD items included in the DSM-IV (American Psychological Association, 1994). The SWAN is designed to assesses both adaptive functioning and maladaptive functioning on ADHD-related behaviors using a 7-point scale. Higher positive scores (i.e. between +1 and +3) represent maladaptive

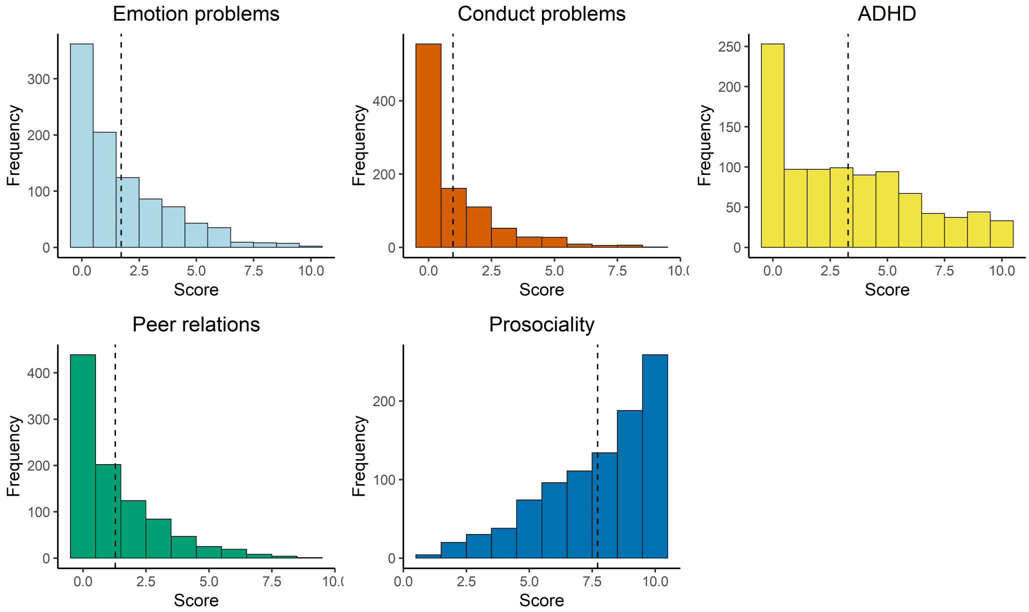

Figure 2. Histograms for teacher-report ratings on SDQ developmental problem domains

functioning, while higher negative scores (i.e. between -1 and -3) represent adaptive functioning (0 = average). For example, scoring a +3 on the item "Sustaining attention" indicates the child has pronounced problems with sustaining attention. The SWAN scale measures items within both the domains of hyperactivity/impulsivity and inattention. For an overview of studies assessing the psychometric properties of the SWAN scale see Brites et al., 2015. We analyzed the teacher-report version of the SWAN scale in our study.

1.4 Statistical analyses

1.4.1 Pre-processing

Handling outliers and missing data. Outliers were identified and replaced with missing values using a two-step process that was identical for all tasks and participants. First, reaction times per task were log-transformed to reduce skewness (Supplementary Material

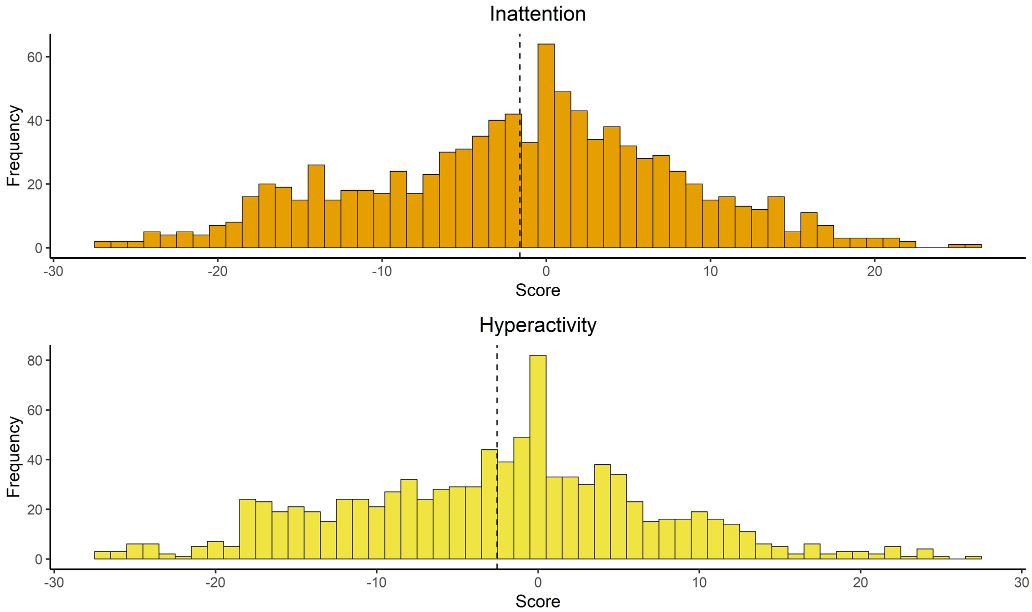

Figure 3. Histograms for teacher-report ratings on SWAN inattention scale and hyperactivity scale

Figures S41-S49). Second, to remove implausible values all reaction times below 100ms were regarded as anticipations and replaced with missing values (Luce, 1986).

1.4.2 Summary of analyses

We conducted the following sequence of analyses. *First*, to capture the high resolution temporal dynamics of response times across trials at the intraindividual level, we used a novel quantitative framework called Dynamic Structural Equation Modeling (DSEM; Asparouhov et al., 2018). DSEM is a broad modeling framework that allows us to estimate static and dynamic characteristics of participants' cognitive performance, interindividual differences in these characteristics, and how they relate to between- and within-person covariates. We wanted to know which statistical parameters are needed to describe people's time series: (a) *response speed* which refers to a person's mean reaction time, (b) *reaction-time variability* which refers to the average amplitude of fluctuations from a person's mean; (c) *inertia* which is the extent to which reaction-time on a current trial can be predicted from reaction-time on a previous trial, and captures the temporal order of fluctuations from a person's mean; (d) *trend* which refers to linear systematic change in a person's mean over time. We also want to know whether people significantly differ from each other in the magnitude of the previously mentioned parameters (a-d).

To answer our questions, we started out by estimating the maximal DSEM model, including all four fixed effects (a-d), each with a random effect capturing individual differences in these parameters. We then specified and compared a series of increasingly simple models that reflect hypotheses about the necessity of dynamic parameters and interindividual differences therein to describe the time series of cognitive performance in our sample. We used the deviance information criterion (DIC; Spiegelhalter et al., 2002; Spiegelhalter et al., 2014) to select among a series of nested models. This allowed us to investigate which of the four parameters were needed to best explain the timeseries in each task, and whether these four parameters needed a random effect (i.e. whether the parameters differ between people);Asparouhov et al., 2018). We selected the models with the lowest DIC.

Second, we wanted to know if interindividual differences in the selected model parameters were related to interindividual differences in age and severity of developmental problems. We added between-person covariates to our models representing age and domains of developmental problems. Age-effects were not hypothesized and were only included to control for well-documented age-differences in reaction-time measures.

Third, we wanted to know which cognitive task produced the reaction-time variability estimate that was *most sensitive* to individual differences in inattention and hyperactivity/impulsivity severity, respectively. We conducted a formal comparison of the relation between severity in inattention symptoms and reaction-time variability across cognitive tasks using a series of Steiger's z-tests (Steiger, 1980).

Finally, we wanted to test which theoretical-mechanisms drive differences in reaction-time variability in children with higher inattention and/or hyperactivity symptom severity by estimating the effect of block-specific differences in cognitive demands. We used a subtractive method by combining the block-wise design of the COTAPP with latent difference score models, which allowed us to estimate the within-person difference in reaction-time variability between pairs of cognitive tasks that differed with regard to a specific manipulation. We will describe all analyses in detail in the succeeding sections.

1.4.3 Model specification

We specified four dynamic structural equation models using Mplus 8.5. (Muthén and Muthén, 2017). The most complex DSEM consisted of eight parameters, which reflect different within-person characteristics of cognitive performance and between-person differences in these characteristics. We thus specified our models at two levels: (a) within-person, capturing individual variation across time, and (b) between-person, capturing variation across individuals.

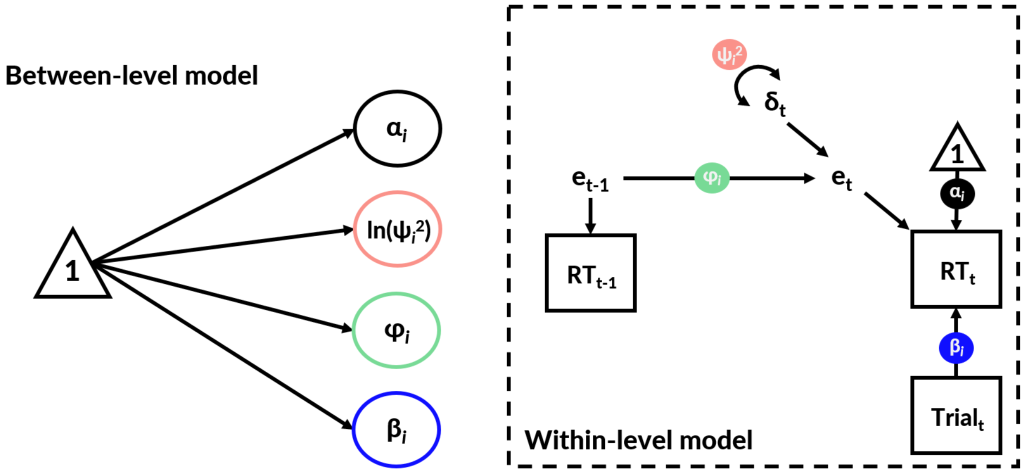

Figure 4. Schematic of full dynamic structural equation model, with all four parameters and random effects. On the left-hand side we can see the within-person part of the model where the four parameters are specified for each person. Each colored dot corresponds to a parameter which together form the function that produces a child's reaction times. The black dot correspond to response speed (denoted a in the "model specification" section). The pink dot corresponds to the reaction-time variability parameter (b). The green dot corresponds to the inertia parameter (c). The blue dot reflects the trend parameter (d). On the right-hand side we can see the between-person part of the model where we specify the sample average for each of the within-person parameters and the extent to which individuals deviate from the average of each parameter, using random effects. Again, the colors denote the same parameters as in the within-person part of the model. The within-person model and the between-person model are both estimated in one step.

At the within-person level, each person's reaction time at trial t (y_{it}) was modeled as the output of the person's mean reaction time over all trials (response speed; α_i), plus a trend capturing a person's linear systematic change in reaction time over the period of the testing block (trend; β_{1_i}), plus the predictability of the person's current reaction time from their reaction time at the prior time point (inertia; ϕ_i), plus the divergence from the person's observed and predicted reaction time at each time point (reaction-time variability; ϵ_{ti}). To ensure stationarity assumptions were met, a special case of DSEM (residual-DSEM) was used to model the inertia and the trend parameters separately (Asparouhov et al., 2018). At the between-person level, all four person-specific parameters were specified as outcomes that reflect the average coefficient for person-specific parameters in the sample and a random-effect that reflects the magnitude of person-specific deviations from this sample average. For example, to model between-person differences in mean reaction time, we use a fixed-effect (γ_{00}) that reflects the average reaction time across all children in our sample and a random effect that reflects the variance of person-specific deviations from this average (u_{0_i}).

Within-level model

$$y_{ti} = \alpha_i + \beta_{1_i} Trial_{ti} + \epsilon_{ti} \tag{1}$$

Between-level model

$$\epsilon_{ti} = \phi_i \epsilon_{(t-1)i} + \delta_{ti} \tag{2}$$

$$\alpha_i = \gamma_{00} + \upsilon_{0i} \tag{3}$$

$$\phi_i = \gamma_{10} + \upsilon_{1i} \tag{4}$$

$$\beta_{1i} = \gamma_{20} + \upsilon_{2i} \tag{5}$$

$$\psi_i^2 = exp(\omega_0 + \upsilon_{3i}) \tag{6}$$

1.4.4 Model comparison

A series of parameter constraints reflecting hypotheses about children's cognitive attributes was assessed using the deviance information criterion (DIC; Spiegelhalter et al., 2002; Spiegelhalter et al., 2014). First, to test the hypothesis that all individuals have the same amplitude of fluctuations in their time series, we constrained the variance of the latent variable capturing individual differences in reaction-time variability (ψ_i^2) to zero. Second, to test the hypothesis that all children's reaction time is equally predictable from their reaction time at the prior time point, we constrained the variance of the inertia parameter (ϕ_i) to zero. Third, we tested the hypothesis that children's reaction time on each trial is independent from their reaction time on the preceding trial, and that this holds for all children in the sample. We constrained the mean and interindividual variation of the inertia parameter (ϕ_i) to zero. Lastly, we tested the hypothesis that all children's mean reaction time is equal by constraining the interindividual differences in the response speed parameter (α_i) to zero. The substantive importance of the trend parameter was not assessed because constraining its mean and/or variability to zero would violate the stationarity assumption for some subjects (i.e. the mean, variance, and autocorrelation do not systematically change over time). This sequence of comparisons was conducted for all blocks independently and the model with the lowest DIC was chosen.

To assess the robustness of our model comparison, we changed the model seed and examined whether the difference in the DIC between two iterations of the same model exceeded the difference in the DIC between the different models (Asparouhov et al., 2018). The DIC supported the most complex DSEM with 8 parameters across all blocks, except blocks 1 and 7B where including the inertia parameter did not improve model fit. The DIC showed good stability under a different seed. For detailed results see Supplementary materials F.

1.4.5 Model estimation check

All models were checked for convergence according to a model diagnostic procedure adapted from the WAMBS checklist (Supplementary materials C; van de Schoot et al., 2021; Depaoli and van de Schoot, 2017). First, we visually inspected trace plots, autoregression plots, and kernel density plots for model convergence. If all three plots supported convergence we doubled the number of iterations of the initially converged models and repeated the same visual convergence inspection. Finally, we compared model parameters between the initially converged model and the model estimated with double the iterations. If there was negligible discrepancy in model parameters between the two models (i.e. $> |\%1|$; Depaoli & van den Schoot; 2017) we concluded that the model converged. All DSEMs converged after a maximum of 40,000 iterations (for detailed results see Supplementary materials D).

1.4.6 Assessing between-person associations

Age as a covariate of DSEM parameters. After we chose the appropriate model we added age as a time-invariant covariate at the between person-level, since reaction-time measures are age-related. We regressed all the latent variables at the between-subject level on age to assess if individual differences in e.g., reaction-time variability were significantly predicted by age. Age, like all subsequently included time-invariant covariates, was grand-mean centered. We grand-mean centered covariates because we wanted to interpret the intercept of the latent variables as the mean (when predictors have a mean of zero due to grand-mean centering, the intercept of the outcome can be interpreted as the mean McNeish and Hamaker, 2020).

SDQ dimensions and age as covariates of DSEM parameters. We added the grand-mean centered total scores of the five SDQ dimensions (emotionality, prosociality, conduct problems, ADHD, and peer relations) as covariates at the between-person level. We regressed all the latent variables at the between-subject level on the SDQ dimensions. Age was also maintained as a between-person, grand-mean centered covariate. All between-person covariates were allowed to covary freely.

SWAN dimensions and age as covariates of DSEM parameters. We specified and estimated a model where the total scores of the two SWAN dimensions (inattention and hyperactivity) and age were, grand-mean centered, between-person covariates. We regressed all the latent variables at the between-subject level on the SWAN dimensions and age. The two SWAN dimensions and age were allowed to covary freely.

Steiger's Z test. We wanted to know which task manipulation produced the reaction-time variability estimate most sensitive to individual differences in the severity of the inattention and hyperactivity symptoms. We used the associations between reaction-time variability from the 2-choice reaction time task and ADHD subdomain scores (i.e. SWAN total scores for inattention and hyperactivity) as the benchmark effect sizes. We tested whether different task manipulations led to an incremental benefit in sensitivity. To formally test the hypothesis that the dependent correlations between reaction-time variability and inattention and hyperactivity severity are equitable across tasks we used a series of Steiger's z-tests, which compare the effect size of interest while taking into account the dependency between reaction-time variability from different tasks (Steiger, 1980). We used the r.test function from the psych package in R to compute Steiger's z-tests (Revelle, 2022).

Latent difference-score models for block comparison. We wanted to test four hypotheses about the mechanisms driving reaction-time variability, and their relation to individual differences in the severity of the ADHD domains of inattention and hyperactivity. We used a subtractive method by combining the unique task-structure of COTAPP with latent difference-score models (McArdle, 2009; Kievit et al., 2018). Five cognitive tasks within the COTAPP use a 2-choice reaction time task at their core and then add various manipulations. This allows us to compare children's reaction-time variability within the 2-choice reaction time task with tasks that differ in the implementation of a specific manipulation. Each task-specific manipulation perturbs a specific cognitive process, which enables us to test the effect that changing this process has on reaction-time variability. Using latent difference-score models, we can assess whether task-specific manipulations lead to within-person differences in reaction-time variability and whether individual differences in the degree of difference, are associated with inattention and/or hyperactivity severity. We used this method to test four mechanistic hypotheses about the causes of reaction-time variability. We compared reaction-time variability from block 2, to block 3, 4, and 7a separately and reaction-time variability in block 7a to block 7b.

After our primary analyses using DSEM we extracted the age- and accuracy-residualized reaction-time variability from each cognitive task, for each person (i.e. we extracted each person's within-person residual variance). We then used these random effects in four latent difference score models to assess the extent of within-person difference in reaction-time variability across the aforementioned task comparisons.

Specification of latent difference-score models. All latent difference-score models were specified and estimated using the lavaan package in R (Rosseel, 2012). In a latent difference-score model with two time points, we conceptualize the score of a person i on the construct of interest at time t as a function of an autoregressive component and some residual.

$$RTV_{it2} = RTV_{it1} + \zeta_{ti} \tag{7}$$

By setting the autoregression to 1, i.e. specifying reaction time variability at the prior time point as a perfect predictor of reaction time variability at the current time point, the residual component is equal to the difference between the two cognitive tasks. The difference is then:

$$\Delta RTV_{it2} = RTV_{it2} - RTV_{it1} \tag{8}$$

We then defined a latent difference-score factor with a factor loading on RT at time t fixed to 1. This allows us to measure the average difference in reaction-time variability across participants between two tasks and individual differences in this difference through the variance component of the latent difference-score factor. Given that the reaction-time variability measured in each task is sufficiently reliable we assume that any change in reaction-time variability can be attributed to one of two factors: (1) the passage of time—training effects and/or fatigue; (2) the task-specific manipulations. To assess the association between individual differences in the degree of difference in reaction-time variability with individual differences in inattention and hyperactivity symptom-severity, we regressed difference scores on the two SWAN dimensions of inattention and hyperactivity.

Inattention and hyperactivity severity were allowed to covary freely. We allowed individual differences in hyperactivity and inattention to covary with baseline reaction-time variability. Lastly, we allowed baseline reaction-time variability and difference-scores to covary, capturing the extent to which the difference between tasks is related to children's reaction-time variability in the baseline task.

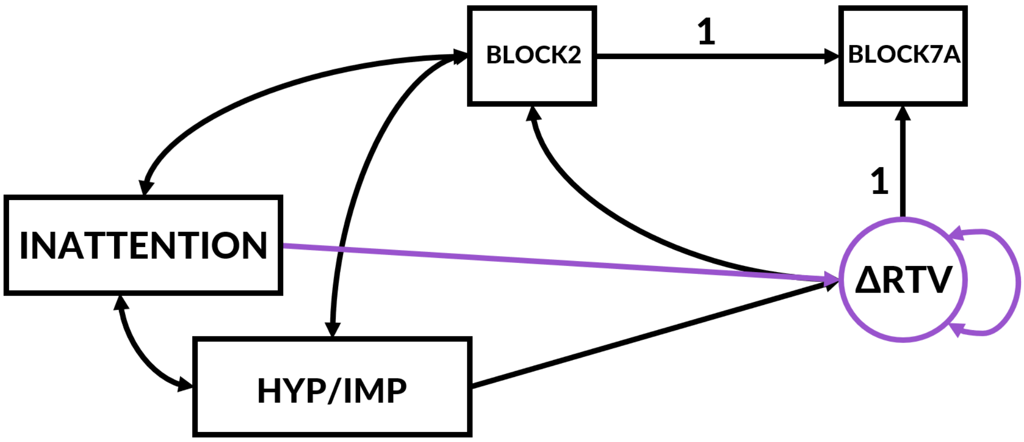

Figure 5. Schematic of latent difference score model used across block comparisons. The parameters in purple denote the parameters of interest. (1) The mean and variance of the latent difference score, represented by a purple circle with "ΔRTV" written inside. These capture the average difference in reaction-time variability that is due to the task-specific manipulation, and individual differences in the degree of difference. (2) The association between differences in inattention severity and differences in the degree of difference in reaction-time variability, captured by the arrow going from the "inattention" box to the purple circle. "BLOCK2" and "BLOCK7A" are placeholder names representing the tasks from where observed scores on reaction-time variability are taken for each task comparison. In this figure the model comparing the 2-choice reaction time task (block 2) with the vigilance choice-reaction-time task (block 7A) is depicted.

Results

Summary of results

Based on the results of our model comparison we used the most complex DSEM with eight parameters reflecting reaction-time variability, response speed, inertia, systematic change in reaction-time and individual differences in these parameters, for all subsequent analyses (see Figure 1 for model schematic). First, we found that age was significantly related to faster response speed and lower reaction-time variability across all cognitive tasks. Age was inconsistently associated with inertia and systematic changes in reaction-time within cognitive tasks (i.e. the relation only held for some tasks). Third, we found that higher reaction-time variability was consistently and specifically associated with greater ADHD severity. Crucially and in contrast with, a global hypothesis, we found that it was not related to any other dimension of behavioral functioning across all cognitive tasks. Fourth, we found that the relation between ADHD and reaction-time variability was specific to severity in the inattention domain across all cognitive tasks. Fifth, we found that all four manipulations led to a substantial within-person difference in reaction-time variability, relative to the baseline task. Greater inattention symptom severity was significantly associated with a greater within-person difference in reaction-time variability after a sustained attention manipulation, but not after any other manipulation. Hyperactivity/impulsivity severity was not significantly associated with individual differences in the extent of within-person difference in reaction-time variability within any task comparison. Finally, we found that a 2-choice reaction-time task administered after a sustained attention manipulation, produced a reaction-time variability estimate which was the most sensitive to severity in inattention symptoms.

Younger children show higher reaction-time variability

Older children consistently responded faster (β_{range}[1] = [-0.479, -0.598], $p_{range} < 0.001$]) and less variably (β_{range} = [-0.155, -0.398], $p < 0.001$) across all tasks. Older children decreased their reaction-time faster across trials (β_{range} = [-0.150, -0.295], p_{range} = [< 0.001, 0.006]), across *most* cognitive tasks, likely reflecting greater learning efficiency. Systematic change in reaction-times was not significantly associated with age, in the simple reaction-time task (β = -0.104, p = 0.078) and the 2-choice reaction-time task (β = 0.021, p = 0.374). This may be a byproduct of the simplicity of these tasks which could have masked age-related difference in learning speed, or may simply reflect the unreliability of the trend parameter across then span of 20-30 trials. Older children's reaction time was, on average, related to lower inertia in the simple reaction-time task (β = -0.157, p = 0.002) and the event-rate choice-reaction time task (β = -0.155, p = 0.019). In the other cognitive tasks, there was no significant association between inertia and age (β_{range} = [-0.121, 0.037], p_{range} = [0.029, 0.286]). All associations between age and DSEM parameters were present after we controlled for accuracy scores, for a detailed summary of our results see Supplement I.

[1] β_{range} and p_{range} indicate the minimum and maximum standardized effect size and p-value across all tasks, respectively.

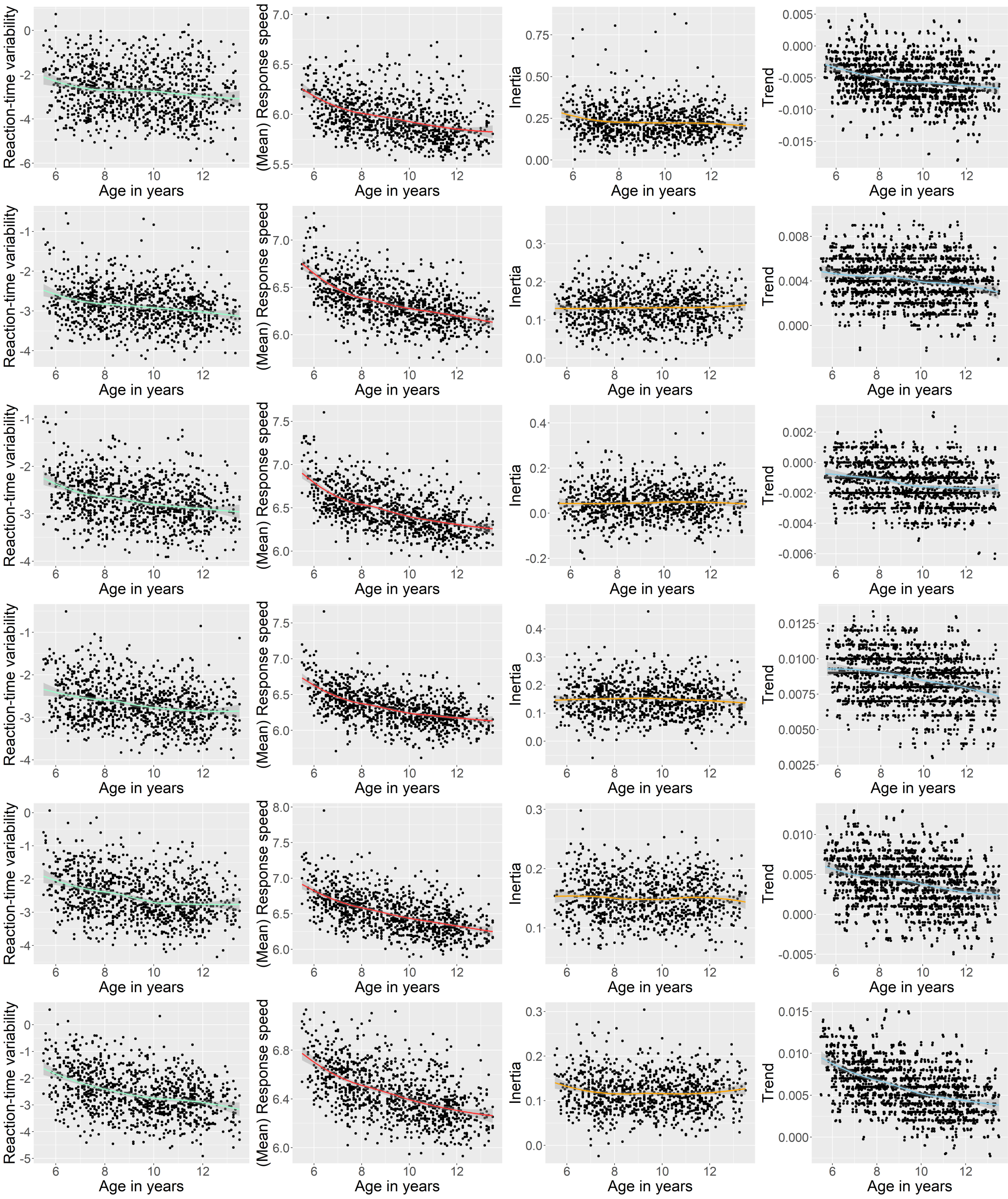

Figure 6. Relationship between individual differences in age and individual differences in DSEM parameters. Each row corresponds to a different task. Tasks are ordered in the temporal order they occurred, with the simple reaction-time task on the top row and the long ITI choice-reaction-time task on the bottom row. Each column represents the association between a different DSEM parameter and age.

Lower accuracy is associated with higher reaction-time variability

Accuracy was measured in the same way in four cognitive tasks, i.e. pressing the key not assigned to the stimulus was coded as an error: the 2-choice reaction-time task, the reward choice-reaction-time task, the vigilance choice-reaction-time task, and event-rate choice-reaction-time task. Results for this subset of tasks if as follows. Children who performed more variably also made more errors, on average, across all cognitive tasks (β_{range} = [0.179, 0.415], $p_{range} < 0.001$). Children who made more errors also performed more slowly on average, across all tasks (β_{range} = [-0.174, -0.437], $p_{range} < 0.001$), together suggesting that a simple speed-accuracy trade-off does not explain individual differences in responses adequately. Children that made more errors also had a higher inertia in three of four cognitive tasks (β_{range} = [-0.113, 0.185], p_{range} = [0.009, 0.018]). In the reward choice-reaction time task ($\beta = 0.029$, $p = 0.286$) there was no significant association between the number of errors and the individual differences in inertia. Differences in the rate of systematic change in reaction-times were not associated with the amount of errors in three of four cognitive task (β_{range} = [-0.033, 0.209], p_{range} = [0.051, 0.418]). In the reward choice-reaction-time task, the a greater linear decrease in reaction times was associated with more errors ($\beta = -0.150$, $p = 0.047$).

The interference choice-reaction time task allowed for two types of errors, compatible errors and incompatible errors. Compatible errors occurred when a child pressed the wrong button in a trial where there was no incongruence between the stimulus location and the response direction. Incompatible errors occurred when there was a mismatch between spatial location and response direction. A greater frequency of errors in incompatible trials was more strongly associated with higher reaction-time variability, faster response speed, and a greater increase in response speed over time, relative to errors made in compatible trials. Errors in incompatible trials were not significantly associated with individual differences in inertia. A greater number of errors in compatible trials were only associated with a faster response speed. For detailed results see Supplement I.

Higher reaction-time variability is specifically associated with greater ADHD severity

We assessed how individual differences in five domains of behavioral functioning, as measured by the Social Difficulties Questionnaire (SDQ), relate to individual differences in response speed, reaction-time variability, inertia, and systematic change in reaction times. The associations between each SDQ dimension and DSEM parameters reflect the unique, age- and accuracy-residualized, relations between children's psychopathology and their cognitive characteristics.

ADHD was the only SDQ-dimension that was consistently associated with individual differences in reaction-time variability. Children with greater ADHD symptom-severity had, on average, higher reaction-time variability (β_{range} = [0.128, 0.229], $p_{range} < 0.001$). Prosociality and conduct problems were only associated with reaction-time variability on one task, the vigilance choice-reaction-time task. These associations were positive but weak and specific to the vigilance choice reaction-time task ($\beta_{prosociality}$ = 0.086, p = 0.009; $\beta_{conduct}$ = 0.105, p = 0.004). Slower response speed was weakly associated with higher ADHD severity across most tasks (β_{range} = [0.071, 0.151], p_{range} = [¡0.001, 0.018]), with exception of the simple reaction-time task (β = 0.050, p = 0.162) and the long ITI choice-reaction-time task (β = 0.103, p = 0.117) where the associations were not significant. Slower response speed was also weakly associated with greater emotional problems in three cognitive tasks (β_{range} = [0.066, 0.081], p_{range} = [0.004, 0.01]), with prosociality in three cognitive tasks β_{range} = [-0.169, 0.067], p_{range} = [0.046, 0.001]), and very weakly with greater peer relation problems in the vigilance choice-reaction-time task ($\beta = 0.072$, $p = 0.041$). Higher inertia was associated with greater emotional problems in the 2-choice reaction-time task ($\beta = 0.193$, $p = 0.005$) and in the reward choice reaction-time task (β = 0.137, p = 0.011). Higher inertia was associated with greater ADHD severity in the interference choice-reaction-time task and the long ITI choice-reaction-time task (β_{range} = [0.139, 154], p_{range} = [0.024, 0.042). Higher inertia was associated with greater peer relation problems (β = 0.134, p = 0.031) in the interference choice-reaction-time task. Children with a greater rate of systematic increase in reaction times also scored higher on prosociality, this was true for the simple reaction-time task (β = 0.236, p = 0.003) and the long ITI task ($\beta = 0.249$, $p = 0.027$). For detailed results see Supplement G.

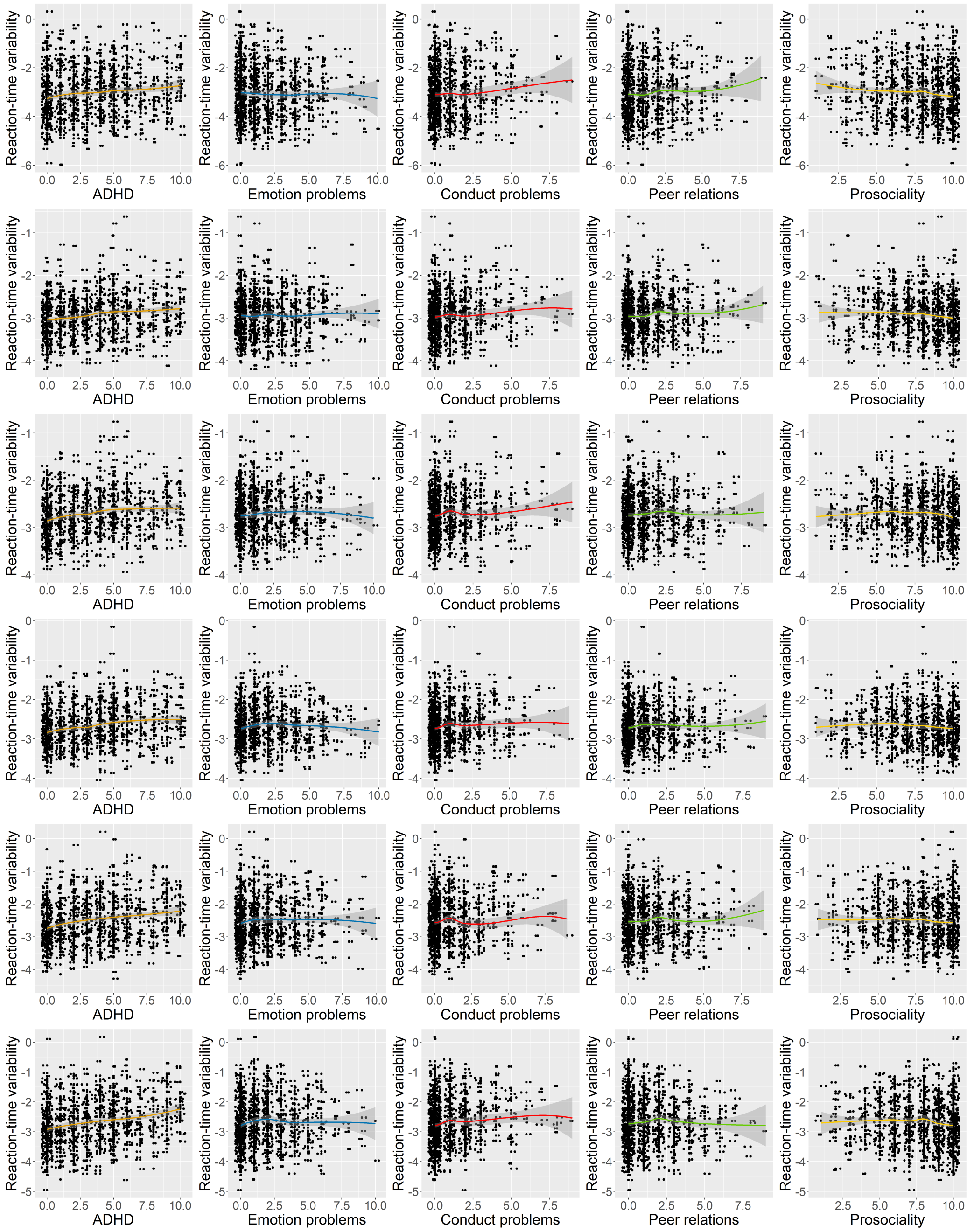

Figure 7. Relationship between individual differences in SDQ developmental problem domains and individual differences in reaction-time variability. Each row corresponds to a different task. Tasks are ordered in the temporal order they occurred, with the simple reaction-time task on the top row and the long ITI choice-reaction-time task on the bottom row. Each column corresponds to a different SDQ domain of developmental problems.

Higher reaction time variability is specifically associated with greater inattention severity

We regressed between-person differences in subdimensions of ADHD symptoms using the SWAN subscales of inattention and hyperactivity/impulsivity on the DSEM parameters, controlling for age and accuracy. Higher inattention severity was specifically associated with greater reaction-time variability across all tasks (β_{range} = [0.144, 0.275], $p_{range} = [< 0.001, 0.002]$). In contrast, hyperactivity/impulsivity severity was not significantly associated with reaction-time variability in any cognitive task. Slower response speed was significantly associated with higher severity in both dimensions, across all tasks. For detailed results see Supplement H.

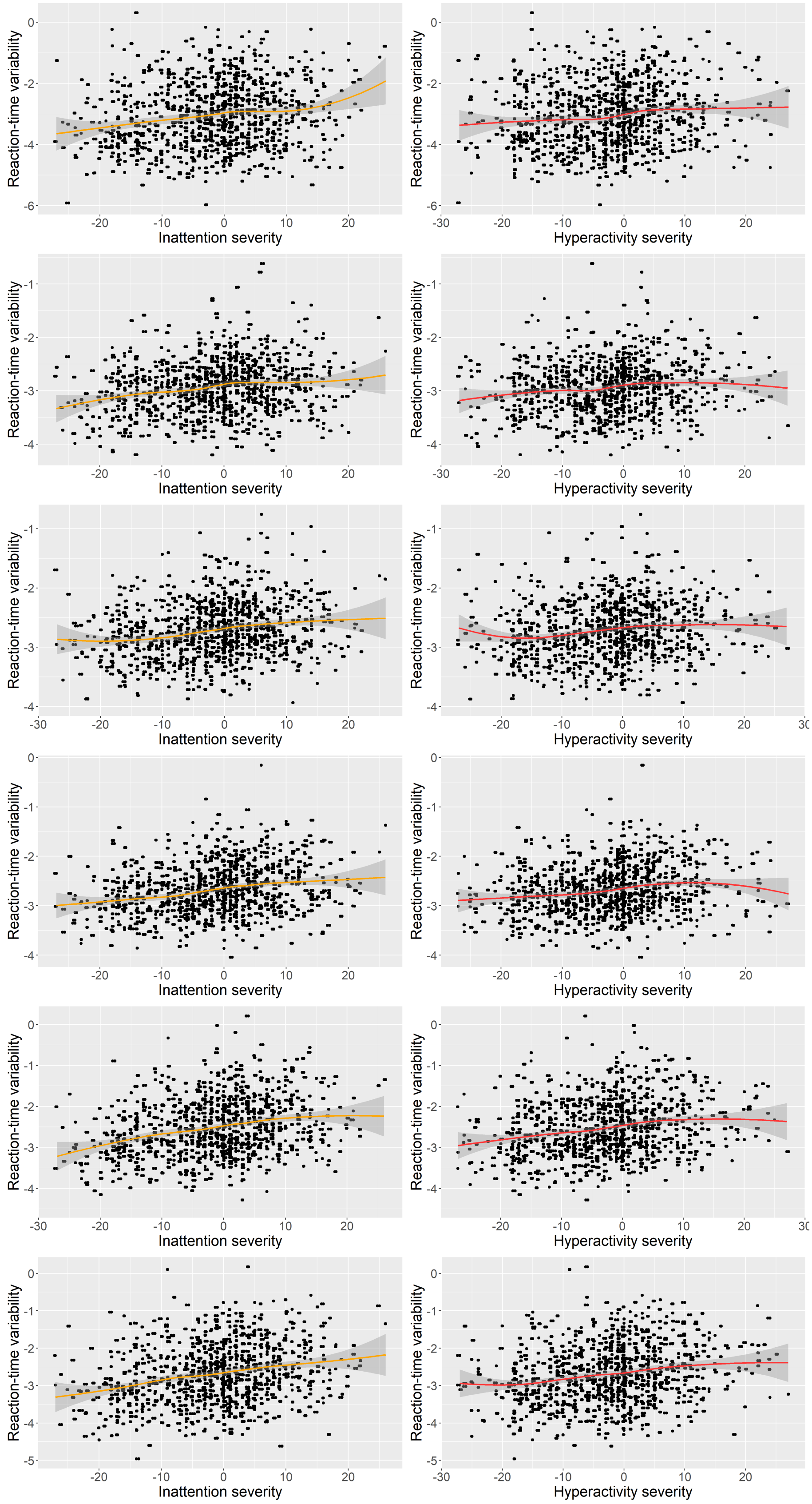

Figure 8. Relationship between individual differences in SWAN subscales of inattention and hyperactivity/impulsivity and individual differences in reaction-time variability. Each row corresponds to a different task. Tasks are ordered in the temporal order they occurred, with the simple reaction-time task on the top row and the long ITI choice-reaction-time task on the bottom row. Each column corresponds to a different SWAN subscale, inattention on the left and hyperactivity on the right.

A 2-choice reaction time task after a sustained attention manipulation provides the greatest sensitivity for inattention severity

We formally compared the sensitivity of reaction-time variability estimates that emerge through different task manipulations to predict inattention symptoms. We used the base 2-choice reaction time task from block 2 as a benchmark as it was the simplest and shortest choice-reaction-time task in the COTAPP testing battery ($r^2 = 0.18$). We found that individual differences in reaction-time variability from the sustained attention choice-reaction-time task were significantly more sensitive to individual differences in inattention symptom-severity, relative to the base 2-choice reaction time task. The increment in effect size was marginal (t = -3.06, $r^2_{difference} = 0.10$, p = 0.002). The long ITI choice-reaction time task was the only other task to have superior sensitivity in comparison to the base 2-choice reaction-time task (t = -2.76, $r^2_{difference} = 0.09$, p = 0.002). However, the difference in sensitivity between the long ITI choice-reaction-time task and the sustained attention choice-reaction-time task was insignificant, indicating that the increment in sensitivity is likely due to the sustained attention manipulation rather than the long ITI (t = 0.47, $r^2_{difference} = -0.01$, p = 0.640).

Taxing vigilance led to a significant difference in reaction-time variability in children with higher inattention severity

We used latent difference score models and a unique task design to isolate the effect of specific cognitive processes on reaction-time variability. We compared a series of modified 2-choice reaction-time tasks with a simple 2-choice reaction-time task (see Figure 5 for a schematic of the design). Each modified 2-choice reaction-time task differed from the standard CRT with regards to one behavioral manipulation. For instance, the reward choice-reaction time task was identical to the 2-choice reaction time task but added rewards. We reasoned that any differences in reaction-time variability between tasks should be predominantly caused by the added behavioral manipulation (e.g. rewards). This allowed us to probe the effect of theoretical mechanisms, tied to task-specific manipulations, on reaction-time variability. For example, an individual might show moderate variability in a simple task, but show substantially more in a more complex task, even more so than others, suggesting the variability in their performance is affected by complexity. We also tested whether individual differences in the degree of difference in reaction-time variability were associated with individual differences in the SWAN dimensions of inattention and/or hyperactivity. Three of four behavioral manipulations led to a significant increase in reaction-time variability, on average. The long ITI choice-reaction-time task did not lead a significant difference in reaction-time variability. There was pronounced individual variation in the degree of difference across all task comparisons (see Supplement K for table). The SWAN dimensions of inattention and hyperactivity were significantly correlated (r = 0.741).

First, the adaptive gain theory predicts that reaction-time variability should decrease under task conditions with high perceived task-utility (Aston-Jones & Cohen, 2005). We reasoned that reaction-time variability should be lower in the reward choice-reaction time task in comparison to the 2-choice reaction-time task. Contrary to expectations, we found a substantial average increase in reaction-time variability ($\beta = 0.301$, $p < 0.001$). Moreover, children with higher inattention or hyperactivity severity should show a greater degree of difference in their reaction-time variability. Contrary to this prediction, children with greater severity in inattention or hyperactivity/impulsivity did not show a greater degree of difference in reaction-time variability ($\beta_{inattention} = 0.042$, $p = 0.367$; $\beta_{hyperactivity} = -0.047$, $p = 0.342$).

Second, the behavioral inhibition model predicts that reaction-time variability will increase in tasks where children have to inhibit a prepotent/ongoing response (Barkley, 1997). In line with this prediction, there was a significant difference in reaction-time variability, on average, following a spatial interference manipulation ($\beta = 0.379$, (p ¡ 0.001). The behavioral inhibition model also predicts that children with higher hyperactivity severity should show a greater degree of difference in their reaction-time variability. In contrast to this prediction, children with greater hyperactivity severity did not show a greater degree of difference in their reaction-time variability ($\beta = -0.024$, $p = 0.625$). Inattention severity was also not associated with the degree of difference in reaction-time variability ($\beta = 0.067$, $p = 0.167$).

Third, according to the adaptive gain theory reaction-time variability should be greater after a prolonged period of testing (here defined as 30 minutes). In line with this prediction, on average, children showed a significant increase in reaction-time variability on the same task, following 30 minutes of testing ($\beta = 0.578$, $p < 0.001$). Individual differences in the degree of difference were significantly associated with higher inattention severity ($\beta = 0.141$, $p = 0.002$), but not hyperactivity severity ($\beta = 0.002$, $p = 0.972$).

Lastly, the cognitive energetic model (CEM) posits that arousal regulation deficits in children with ADHD underlie variability and that this can be exacerbated by increasing the time between trials (Sergeant, 2000). Increasing the intertrial interval from 450-750ms to 3000-6000ms led to a significant decrease in children's reaction-time variability, on average (β = -0.041, p = -0.041). Moreover, contrary to predictions of the CEM, the degree of difference was not significantly associated with inattention severity ($\beta = 0.024$, $p = 0.621$) or hyperactivity severity ($\beta = 0.038$, $p = 0.459$).

Discussion

We found that reaction-time variability was specifically associated with symptom-severity in the inattention domain, in a population-based sample of children aged 5.5 to 13.5 years. Children with higher severity of inattention symptoms performed more variably across all cognitive tasks. Whereas reaction-time variability was not consistently associated with any other domain of behavioral functioning, including hyperactivity/impulsivity symptoms, highlighting the specificity of this association. Moreover, the tendency of children with more severe inattention symptoms to perform more variably held independently of the significantly higher variability showcased by younger children. Our results are, at first sight, at odds with a meta-analysis of 71 studies which concluded that reaction-time variability is a general marker of clinical functioning, and not specific to ADHD (Kofler et al., 2013). It is noteworthy, however, that this meta-analysis is largely composed of studies (63 out of 71 studies) relying on the intraindividual standard deviation (iSD) as a proxy of reaction-time variability which is known to conflate multiple sources of variance, such as systematic changes in reaction time (Wang et al., 2012; Nesselroade and Salthouse, 2004; Prathiba, Shammi et al., 1998). The muddled nature of this statistical proxy may reduce the specificity of its associations. That is, the association between the iSD and mental disorders may be driven by processes that are distinct from the theoretical construct of reaction-time variability, but are nonetheless subsumed by the statistical tool used to quantify it. Alternatively, a symptom-level explanation may be able to reconcile these distinct findings. It is plausible that clinical controls (i.e. people with diagnoses other than ADHD) within the reviewed studies, also suffered from inattention symptoms to a similar extent as people in the ADHD samples.

This is congruent with our findings that reaction-time variability is specific to the inattentive symptoms within the disorder. This possibility also aligns with the finding that ASD patients without comorbid ADHD-symptoms did not show elevated reaction-time variability (Karalunas et al., 2014). Moreover, a previous study supporting the specificity of reaction-time variability as a marker for ADHD split their sample into non-overlapping diagnostic groups (Salum et al., 2019), which are uncommon in clinical populations (Caspi and Moffitt, 2018). Hence, to understand the mechanisms that drive specific aspects of phenotypes associated with neurodevelopmental disorders, it would be beneficial to pay attention to the symptom-level specificity which these mechanisms may display, to avoid decreasing both the sensitivity and specificity of our understanding. Contrary to the possibility that reaction-time variability may be tied to inattention symptoms, a comparison between hyperactive/impulsive and inattentive subtypes of ADHD across 41 studies showed neither subdomain of ADHD was preferentially associated with reaction-time variability (Kofler et al., 2013). However, these findings also suffer from heavy reliance on the intraindividual standard deviation, in 34 out of 41 studies. We interpret the aggregate of past and present results as compelling evidence against the hypothesis that reaction-time variability is a general marker of psychopathology. A weaker version of this hypothesis, where reaction-time variability is a marker for clinical functioning in a distinct subset of symptoms that we did not measure, remains unaffected by our results. Future work should seek to test how robust the association between reaction-time variability and inattention is to the addition of psychopathology symptoms not assessed in our study using a substantively motivated estimate of reaction-time variability.

To further our knowledge of reaction-time variability we used the unique design of the COTAPP assessment battery to test four hypotheses about the mechanisms of reaction-time variability. Two of these hypotheses were derived from the adaptive gain theory (Aston-Jones & Cohen, 2005), and the other two from the behavioral inhibition deficit model (Barkley, 1997) and the cognitive energetic model (Sergeant, 2000), respectively. Our findings support changes in sustained attention as a causal mechanism driving reaction-time variability. This was one of the outcomes predicted by the adaptive gain theory, which posits that reaction-time variability is a byproduct of locus-coeruleus norepinephrine (LC-NE) activity (Aston-Jones & Cohen, 2005). Specifically, the adaptive gain theory predicts that fatigue should push the activity of LC-NE towards the extremities of the arousal curve (inverted U) where children experience an increase in attentional lapses due to mind-wandering, mind-blanking, or increased sensitivity to external distractions (Unsworth & Robinson, 2016; 2018). Our results support the behavioral prediction of the theory, but offer no direct evidence for the implication of LC-NE activity. As a complement to our results, empirical investigations of LC-NE activity as a function of time-on-task show the same behavioral pattern and link this to the diminution of (both tonic and phasic) LC-NE activity using pupillometry (Unsworth & Robinson, 2016; 2018). Together these results support LC-NE driven attentional lapses as a cause for reaction-time variability.

Our results further show that the effect of fatigue on sustained attention is greater in children with greater severity of symptoms in the inattention domain, but not the hyperactivity domain. The temporal instability of reaction-time variability in children with higher inattention symptoms is worth highlighting since it pushes against a static conceptualization of ADHD symptoms that are either absent or present within a child. Children's attentiveness waned over the course of 30 minutes in response to environmental demands which opens the possibility that other behaviors, which may traditionally be considered fixed, also fluctuate over time (e.g. in the span of minutes, hours, or days). Information about the stability of symptoms, and individual differences therein, may point to differences in mechanisms driving ADHD and their contextual sensitivity. This information can be used to fortify the theoretical rationale for interventions, increasing the probability of success and the efficiency of resource allocation.

Contrary to a prediction of the adaptive gain theory, adding extrinsic rewards to the choice reaction-time task did not lower reaction-time variability. In fact, on average, reaction-time variability increased after the manipulation. It is noteworthy, however, that this task was designed to make children respond fast and accurate using incentives. Pushing the speed of children while increasing their motivation using rewards could have led most children to respond more variably than usual because they were operating near their limit, even if their attention was focused on the task. This is congruent with findings showing increased reaction-time variability as a function of cognitive load (e.g. Galeano Weber et al., 2018) and urges future research to retest this hypothesis using incentives that do not alter task demands. Alternatively, the observed pattern could be attributed to ceiling effects. Most children could have already been sufficiently motivated to perform the task and their LC-NE activity was in a phasic state (i.e. exploitative mode), resulting in already low reaction-time variability. Contrary to this explanation, we did not find an association between severity in inattention or hyperactivity/impulsivity symptoms and reward-driven change in reaction-time variability. Adaptive gain theory hypothesizes that children with attention deficit disorders are characterized by overly persistent tonic activation (Aston-Jones & Cohen, 2005; Aston-Jones et al., 1999). Thus, we would expect that rewards would shift these children to a phasic state and lower their reaction-time variability. It may be that children with inattention symptoms, but not necessarily hyperactivity symptoms, reside predominantly in the lower bound of the LC-NE curve where tonic and phasic activation are both relatively low (i.e. a drowsy, inattentive state). This is also congruent with evidence from pupillometry studies showing that low tonic pretrial arousal predicted higher reaction-time variability; the link with inattention severity was, however, not examined (Grandchamp et al., 2014; Mittner et al., 2014). Aston-Jones& Cohen, (2005), are explicit in their description of how ongoing evaluations of stimulus significance affect transitions between the middle portion (phasic state) and the right bound (tonic state) of the LC-NE curve, but do not explicitly convey how the lower bound is affected by this evaluation process. Future studies using a proxy of LC-NE activity and symptom-level measures of ADHD could modulate reward-value to observe the effect of changes in stimulus significance on arousal and reaction-time variability, and how this is moderated by symptom severity.

We tested two more candidate mechanisms. First, the behavioral inhibition deficit (BID) model is a prominent theory of ADHD that claims behavioral inhibition deficits either directly cause reaction-time variability, or indirectly by taxing executive functions (Barkley, 1997). The BID model's predictions were partly supported by our results. We found evidence for the implication of behavioral inhibition as a process driving reaction-time variability, since adding a spatial interference manipulation led to substantial increase in reaction-time variability. However, we did not find evidence for a link between behavioral inhibition and severity in hyperactivity symptoms. Barkley proposed that only children with hyperactivity symptoms possess behavioral inhibition deficits and that these deficits in turn cause their inattention symptoms (1997). He further posits that these secondary symptoms of inattention are qualitatively distinct from the inattention found in the pure-inattentive type of ADHD. Thus, the BID model predicts that hyperactivity must be associated with reaction-time variability, but an association with inattention is optional. Our findings do not lend support to this prediction.

Second, we tested a prediction made by the cognitive energetic model (CEM): Arousal regulation deficits should lead to higher reaction-time variability via an increase in attentional lapses (Sergeant, 2004). Note, that the arousal within the CEM is conceptually distinct from the norepinephrine functioning in the adaptive integration theory, which is more closely aligned with the concept of effort within the CEM (Karalunas et al., 2014). The observed effect was in the opposite direction than predicted and the magnitude of the difference was negligible (i.e. reaction-time variability decreased on average and effect was not significant). Moreover, inattention and hyperactivity severity were not associated with the degree of difference in reaction-time variability. Thus, we found no evidence that arousal regulation as conceptualized by the CEM underlies reaction-time variability in children with ADHD symptoms. Our findings are consistent with most studies in the literature which find that the construct of effort is more consistently related to reaction-time variability than is arousal (Karalunas et al., 2014).

After we used the distinct block-design of COTAPP to tease apart candidate mechanisms, we decided to examine the translational question from a simpler perspective: We asked which task most strongly relates to inattention severity. The choice-reaction time task with a sustained attention manipulation had superior sensitivity according to our formal comparison. Therefore, retesting children after prolonged cognitive effort is an effective tool to increase the sensitivity of reaction-time variability to differences in inattention severity. From a practical standpoint, clinicians looking to add a measure of reaction-time variability into their clinical toolset, may want to consider whether the increase in variance explained is worth the additional financial and time burden associated with a 30m testing battery as opposed to a 5 minute test. Future studies designed to compare the cost-benefit ratio of tasks would go a long way in ensuring the efficient dissemination of reaction-time variability as a tool in the clinic.

The limitations of our study qualify our conclusions and concurrently point to directions for future research. First, our sample reflects the population of children in the Netherlands aged 5.5 to 13.5 years. We encourage readers to thoughtfully generalize inferences to populations they deem share pertinent characteristics with our population. It is noteworthy that the COTAPP is not language or culture sensitive, which should aid generalizations.

Second, dynamic structural equation models assume a Gaussian distribution. We log-transformed reaction-time data to approximate a Gaussian distribution, but further research is needed to test the consequences of violating this assumption.

Third, we wanted to examine the specificity of reaction-time variability as a marker of ADHD and used the SDQ which covers some of the most important developmental problem domains. However, we did not assess an exhaustive list of psychopathology symptoms. Future studies including a comprehensive assessment battery of psychopathology would supplement our findings.

Fourth, the causal inferences made from our latent difference-score models are limited by the fact that we could not control for the temporal effects of fatigue and/or practice effects across blocks. This criticism is not pertinent to the causal inference made with regards to sustained attention deficits, where fatigue was the intended manipulation.

Fifth, we modeled symptom clusters as total scores which do not reflect the association of symptoms with their underlying causal latent dimensions, if these exist. The bias in the estimate of our ADHD variable would be proportional to the difference between the homogeneous weights assigned by total scores and the relative weights assigned by a more appropriate factor model (Bollen and Bauldry, 2011). Under a different causal theory of mental disorders (e.g. network theory; Borsboom et al., 2016), where symptoms are not underpinned by a unitary cause we would ideally have multi-item data for separate symptoms to deal with measurement error without assuming a latent causal factor.

Lastly, our model comparisons relied on the DIC, which has known problems with its instability (Asparouhov et al., 2018). We assessed the stability of the DIC, which was sufficient for all model comparisons. Currently, DSEM has no better alternative metrics for model fit, which points to a clear priority for further methodological work.

The field of ADHD research exemplifies how intraindividual variability has come a long way from the heretical proposal of a few theorists to become an invaluable piece of the developmental puzzle. Today we have the tools to push forth our understanding of within-person variability in cognitive performance and embed this source of individual differences in longitudinal contexts to understand developmental change at an unprecedented temporal granularity. We believe that a close dialogue between neuroscience, clinical psychology, and psychometrics can ensure that our empirical tests are aligned with our theoretical understanding of neurodevelopmental disorders and their cognitive mechanics. In the present paper we exemplified how such an approach can produce novel insight about existing substantive questions.

To conclude we derive three testable hypotheses from the discussion of our data:

First, reaction-time variability is specifically associated with inattention symptom-severity, and not hyperactivity/impulsivity severity, in choice reaction-time tasks. Based on our discussion we further predict that this pattern will hold irrespective of diagnostic status. Which specific symptoms within the inattention domain best predict the magnitude of reaction-time variability remains an open questions for future research. Second, symptoms of ADHD will show meaningful fluctuations across time and people will differ in the extent of these fluctuations. This hypothesis is appreciably broad, but current evidence does not allow us to make more granular predictions. The availability of ecological momentary assessment (EMA) makes it possible to test the age-old assumption that diagnoses are static. Even if symptoms ultimately revert to their mean after a short-period of time, the informativeness of differences in the patterns of temporary changes is worth investigating. Examining how differences in symptom fluctuations relate to socially relevant and widely accessible outcomes, such as academic performance, would offer a pertinent test of this hypothesis. Third, children with higher inattention severity will show lower pretrial LC-NE activity which will mediate the association between symptom severity and reaction-time variability. We hope that researchers will be inclined to follow one of our proposed trajectories, or create their own path to enter the exciting world of dynamics that unfolds at each step of a child's development.

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Supplementary materials

Supplement A: Detailed description of testing battery

One-choice reaction time task (block 1). A one-choice reaction-time task requires the participant to respond to a stimulus as soon as it appears on the screen and the reaction time of the participant is recorded. One stimulus appears in each trial and there is only one response key that can be pressed. In the COTAPP the stimulus shows up in the center of the screen after an intertrial interval that varies between 400-750ms. This block consists of 6 practice trials and 20 test trials. The practice trials are completed under the experimenter's supervision and participants receive auditory feedback when they respond prematurely (i.e. the response is faster than 150ms). No feedback is given during the test trials. The practice block is automatically repeated if the participant logs 3 or more premature responses. If the experimenter perceives that the participant needs more practice to comprehend the task the practice block can be repeated. The testing block is never repeated.

Two-choice reaction-time task (block 2). In the two-choice reaction-time task in block 2, participants encounter two stimuli across the trials. One type of stimulus is presented on each trial with each stimulus being presented equally often. The order of stimulus presentation follows a non-discernible pattern and is fixed across repeated assessments. Each stimulus is linked to a directional response key (i.e., right, or left arrow key). Stimuli are presented in the center of the screen and the associated key must be pressed as fast as possible. Accuracy per block and response speed per trial are recorded. The intertrial interval varies between 400-750ms. Block 2 includes six practice trials and 30 test trials. Auditory feedback is provided for every error in the practice block, per trial, but not during the testing trials. The practice block is automatically repeated if the participant logs 3 or more premature responses (<150ms). The practice block can also be manually repeated if the experimenter deems the participant requires more feedback. The testing trials are automatically repeated once, if the participant logs 4 or more premature responses (<150ms) to ensure that participants learn stimulus-response associations before proceeding to subsequent blocks.

Two-choice reaction-time task with dynamic reinforcement algorithm (block 3). The two-choice reaction-time paradigm is identical to block 2. Block 3 diverges from block 2 with the addition of a reward that is used to incentivize acceleration in reaction speed. An algorithm is used to provide a reward to participants that respond correctly within an allotted time frame, which is based on their performance during block 1. Thus, based on their performance participants' trials are split into two types with different consequences. Rewarded trials are trials where participants respond correctly within the allotted time. Rewarded trials earn participants 1 point, accompanied by visual (trophy animation visible for 2000ms) and auditory feedback (ping sound). Points are added to the participant's total, which is displayed on the top-right of the screen for the duration of the block. After a rewarded trial, the allotted response time is decreased by 20ms, making it more difficult to obtain a point in the next trial without accelerating performance speed. Unrewarded trials are trials where participants respond either too slow or incorrectly. Unrewarded trials do not award participants any points and the allotted response time is increased by 20ms, making it easier to obtain points in the succeeding trial. Block 3 consists of 6 practice trials and 40 test trials. The practice trials can be repeated if the experimenter deems the participant needs more practice. The test trials are never repeated.

Two-choice reaction-time task with congruent and incongruent stimuli (block 4). The two-choice reaction-time task is identical to block 2 with the exception that stimuli are now presented on the left or right side of the screen, instead of always appearing in the center. This creates an incongruency between the spatial location of the stimulus and the direction of the arrow key that is linked to it. Therefore, trials are split into two types. Congruent trials are trials where the direction of the key and the spatial location of the stimulus are the same (e.g. the stimulus linked to the right arrow appears on the right side of the screen). Incongruent trials are trials where the direction of the key and the spatial location of the stimulus are not the same (e.g. the stimulus linked with the left arrow appears on the right side of the screen). Block 4 consists of 6 practice trials and 40 test trials. The practice trials can be repeated if the experimenter deems that the participant needs more practice. The test trials are never repeated.

Two-part two-choice reaction-time task (block 7): Part one of block 7 is identical to block 2. However, at this point in the testing procedure the participant has already completed approximately 20 minutes of cognitive testing. Therefore, a comparison of performance between block 7 (part 1) and block 2 allows for the assessment of effects that accompany a long testing period (e.g., sustained attention). Part one is composed of 6 practice trials and 30 test trials. The experimenter can decide to repeat the practice trials if they deem the participant needs more practice. The test trials are never repeated. Part two of block 7 is identical to block 2, except for a substantial increase in the range of the intertrial interval from 400-750ms to 3000-6000ms. The increased duration between trials makes it more difficult to sustain alertness and keep focused on the task. Part 1 transitions automatically to part 2 without any notification. Part 2 is composed of 20 test trials, which are never repeated.

Supplement B: Raw and log-transformed RT distributions

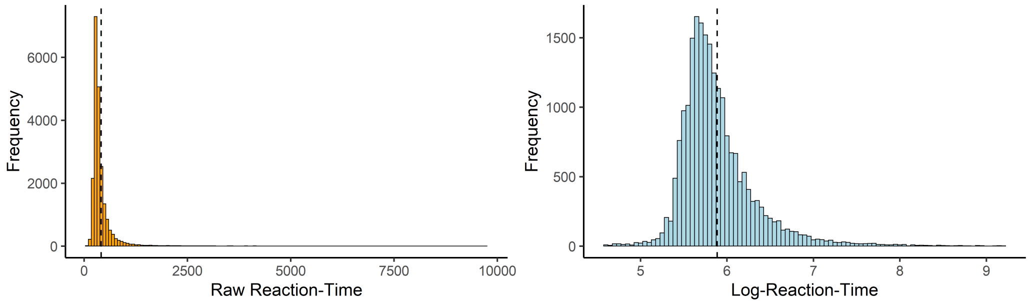

Figure SB1. Histogram of raw and log-transformed reaction-times block 1

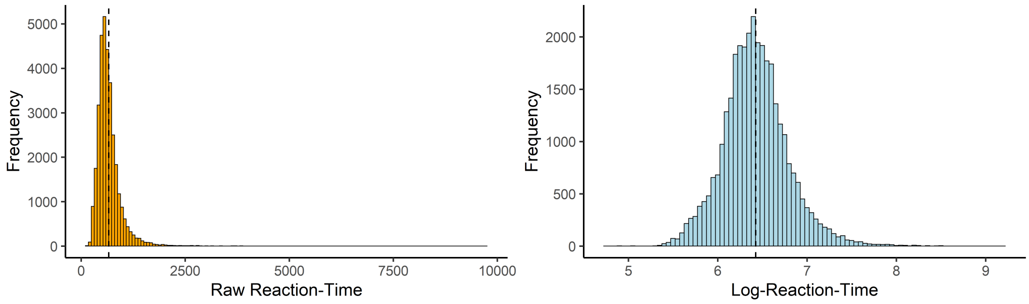

Figure SB2. Histogram of raw and log-transformed reaction-times block 2

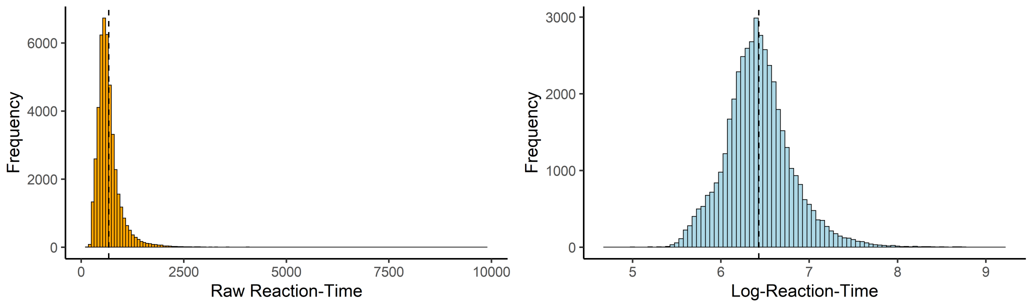

Figure SB3. Histogram of raw and log-transformed reaction-times block 3

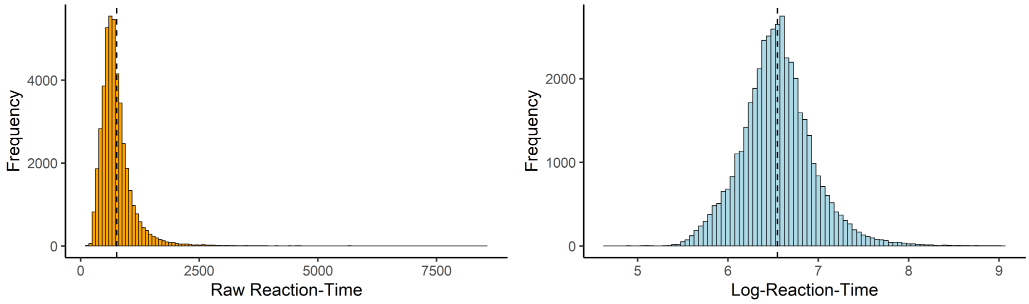

Figure SB4. Histogram of raw and log-transformed reaction-times block 4

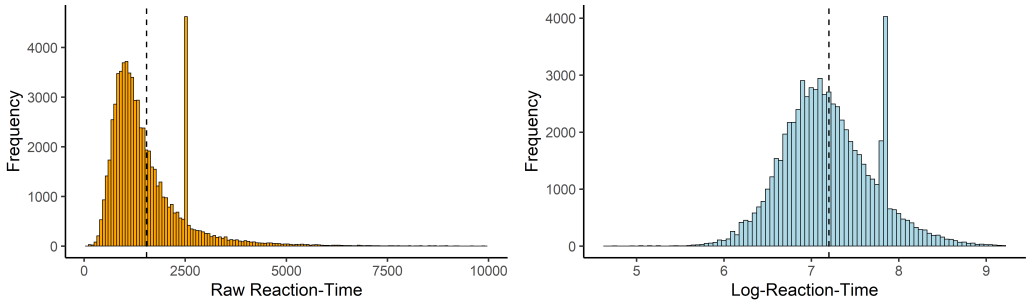

Figure SB5. Histogram of raw and log-transformed reaction-times block 5

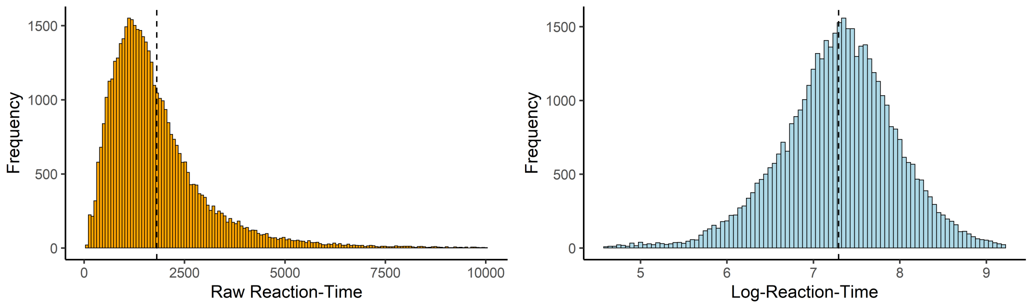

Figure SB6. Histogram of raw and log-transformed reaction-times block 6

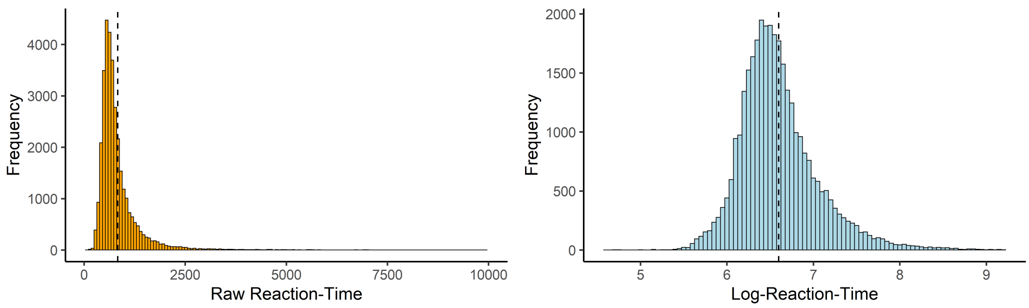

Figure SB7. Histogram of raw and log-transformed reaction-times block 7A

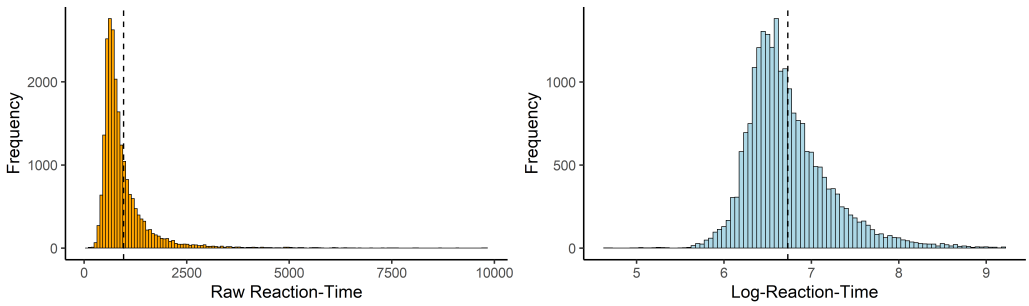

Figure SB8. Histogram of raw and log-transformed reaction-times block 7B

Supplement C: DSEM model diagnostics

Add this MPLUS code to your script to get all the necessary plots.

PLOT: TYPE IS PLOT 2;

Check traceplots for initial convergence

(1) Your traceplot should look like Figure 1.

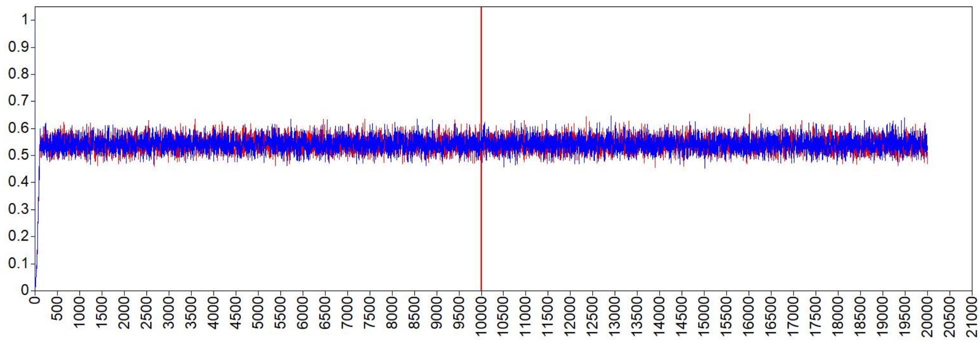

Figure SC1. Example of traceplot that converged.

Check autocorrelation plots for initial convergence

Auto-correlation should be low. A common heuristic is ¡.20. If auto-correlation is high some people use thinning, but there's a paper that's very against much against it (Link & Eaton, 2012). Also, some people say that if all convergence-wise is good then it can be ignored but it's good practice to try to figure out why auto-correlation between iterations is high.

"*If the chains have high levels of dependency, but convergence was obtained and the* *model was estimated properly otherwise, then autocorrelation can be ignored. However, if the patterns of autocorrelation suggest other estimation problems, or problems with the specification of the model, then model modification may be necessary.*" (Depaoli van Schoot, 2017).

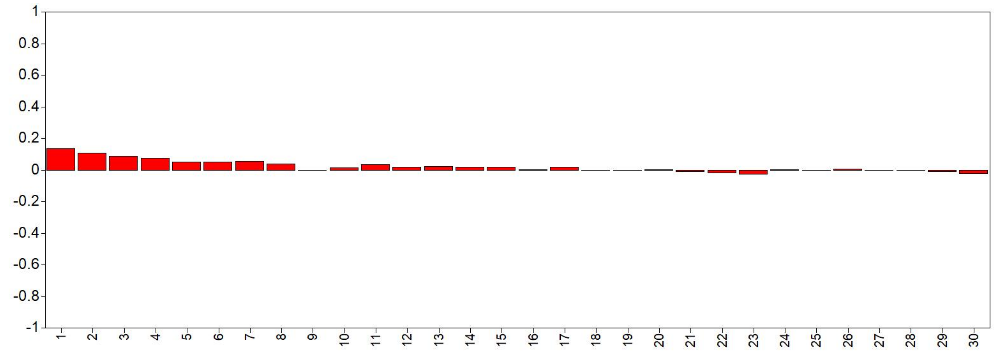

Figure SC2. Example of autocorrelation plot showing low dependency between successive iterations.

Check if Kernel density plot makes sense

It should be relatively smooth, unimodal, and the variance of the parameter should not exceed plausible limits, the range of the parameter should not be larger than e.g. the range of reaction times. It should like Figure 3.

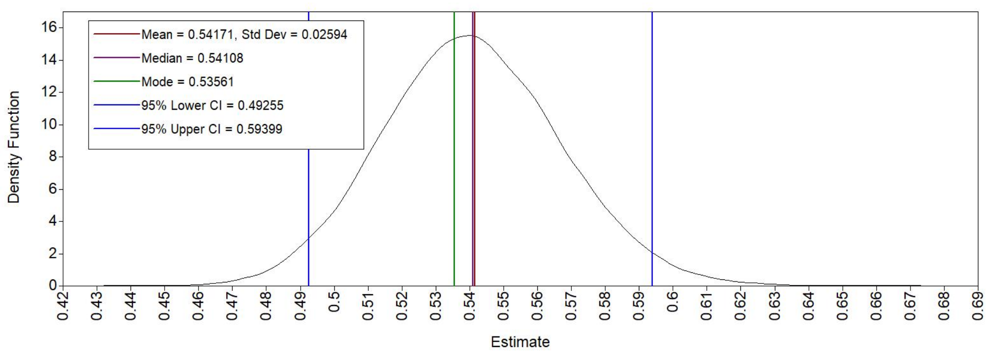

Figure SC3. Example of Kernel density plot that is smooth, unimodal, with sensible variance and range of parameters.

Check for local convergence

1. Double your iterations and check all plots again.

2. If things don't look good, double iterations and try again (discard the first model and do a comparison between the double-iteration model and a new model with 4x the initial iterations).

3. Calculate relative bias in parameters between initial model and double-iteration-model

$bias = 100 * \frac{initialconvergedmodel - modelwithdoubleiterations}{initialconvergedmodel}$

Interpret bias relative to parameter size and substantive considerations. If bias is worryingly high, double iterations and try again.

DIC stability check

Run the initially converged model with a different seed and check the stability of the DIC. I think if the difference in the DIC is smaller than the difference between models we can be relatively safe in the interpreation of our comparison.

"*In such cases, the imprecision that remains could be bigger than the DIC difference in the models we are trying to compare. Therefore, we recommend verifying that the DIC* *estimate has converged by running the MCMC estimation with different random seeds for the same model, and comparing the DIC estimates across the different runs to evaluate the precision of the DIC.*" (Asparouhov, Hamaker, Mouthen, 2018).

Supplement D: DSEM diagnostic results

Table 1. Block 1 relative bias

	Parameters	Initial Estimates	Estimates After 2x Iterations	Relative Bias
Means	LOGRT	5.967	5.967	0.0000000
Means	PHI	0.230	0.230	0.0000000
Means	LOGV	-2.731	-2.732	-0.0366166
Means	TREND	-0.005	-0.005	0.0000000
Variances	LOGRT	0.062	0.062	0.0000000
Variances	PHI	0.030	0.030	0.0000000
Variances	LOGV	1.354	1.354	0.0000000
Variances	TREND	0.000	0.000	NaN

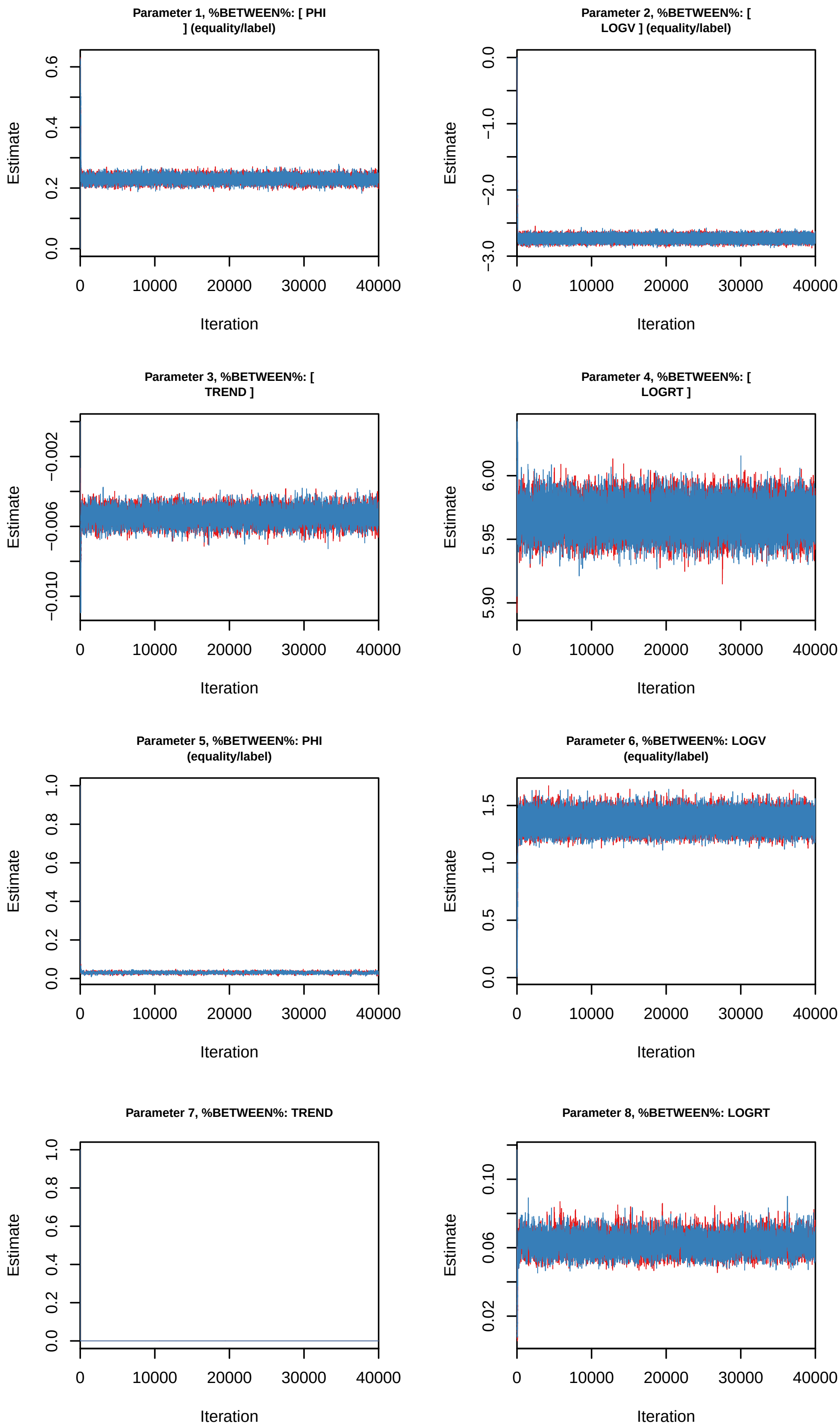

Figure SD1. Traceplots for Block 1 parameters

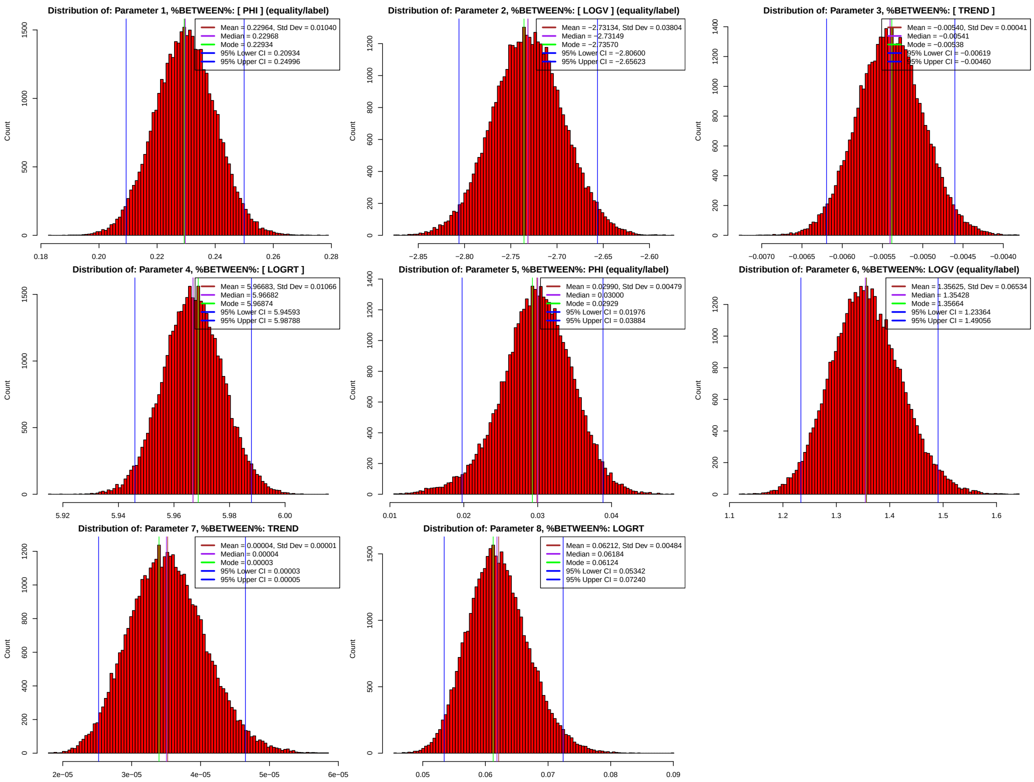

Figure SD2. Bayesian distribution for Block 1 parameters

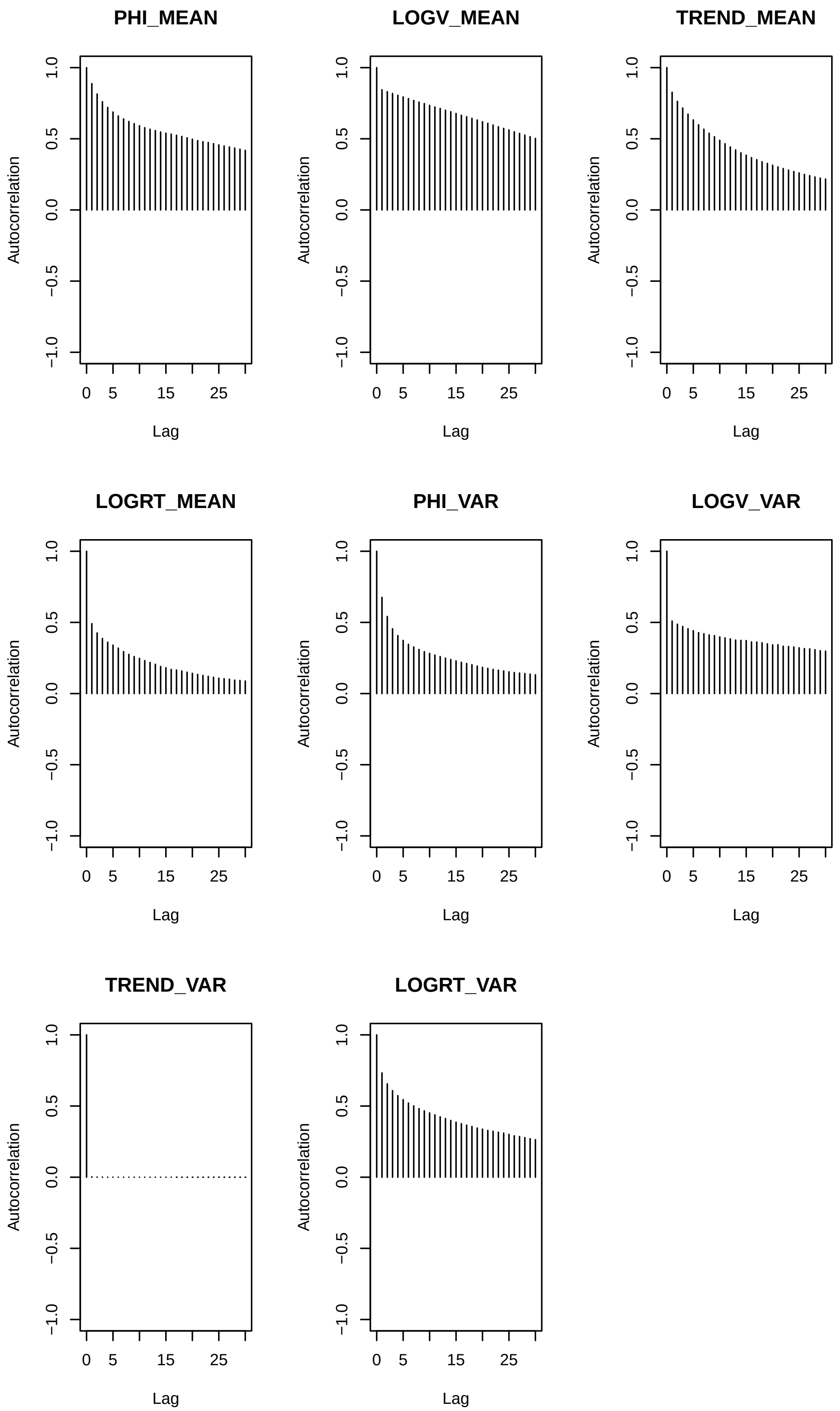

Figure SD3. Autoregression plot for Block 1 parameters

Table 2. Block 2 relative bias

	Parameters	Initial Estimates	Estimates After 2x Iterations	Relative Bias
Means	LOGRT	6.337	6.337	0.0000000
Means	PHI	0.133	0.133	0.0000000
Means	LOGV	-2.869	-2.870	-0.0348554
Means	TREND	0.004	0.004	0.0000000
Variances	LOGRT	0.059	0.059	0.0000000
Variances	PHI	0.011	0.011	0.0000000
Variances	LOGV	0.321	0.321	0.0000000
Variances	TREND	0.000	0.000	NaN

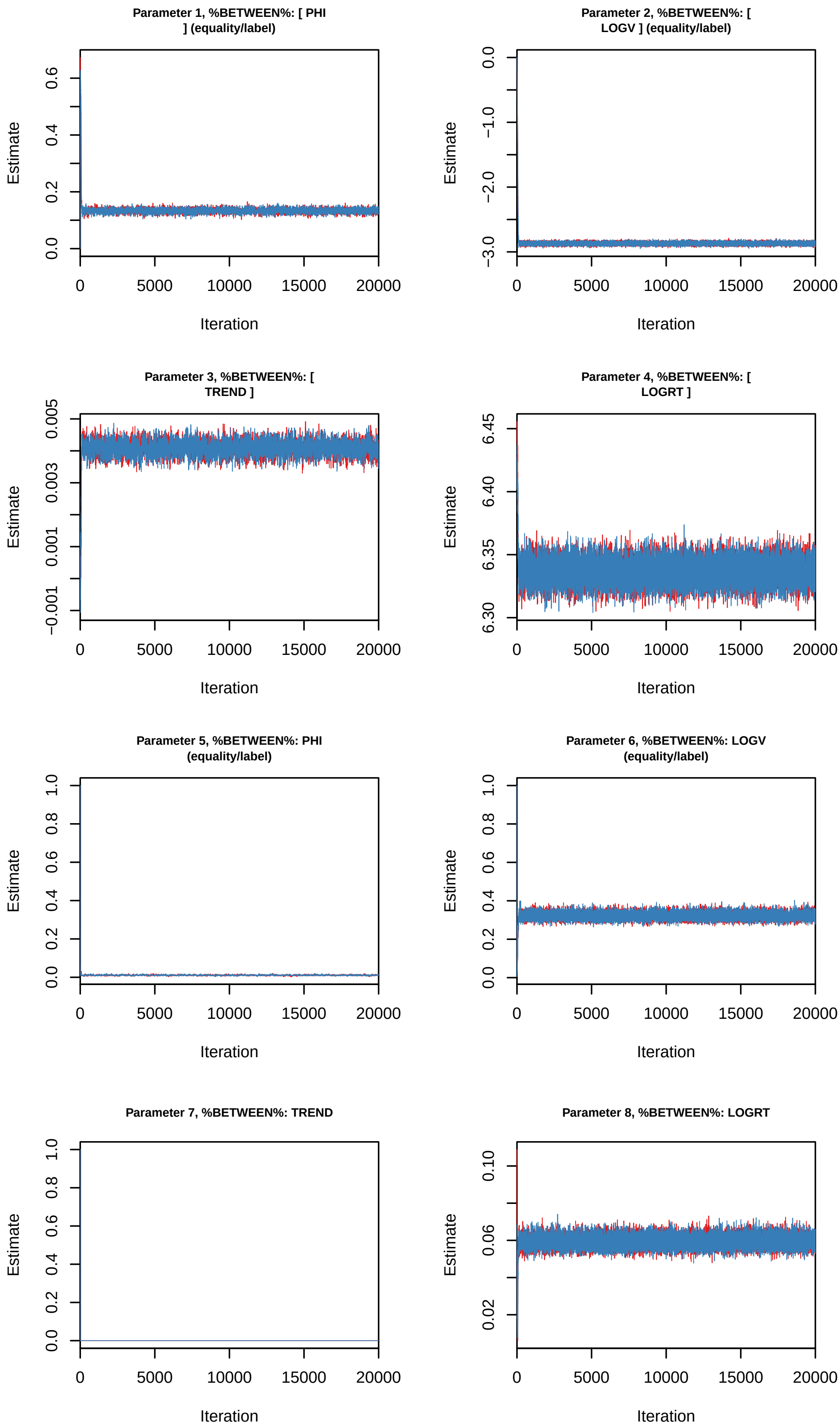

Figure SD4. Traceplots for Block 2 parameters

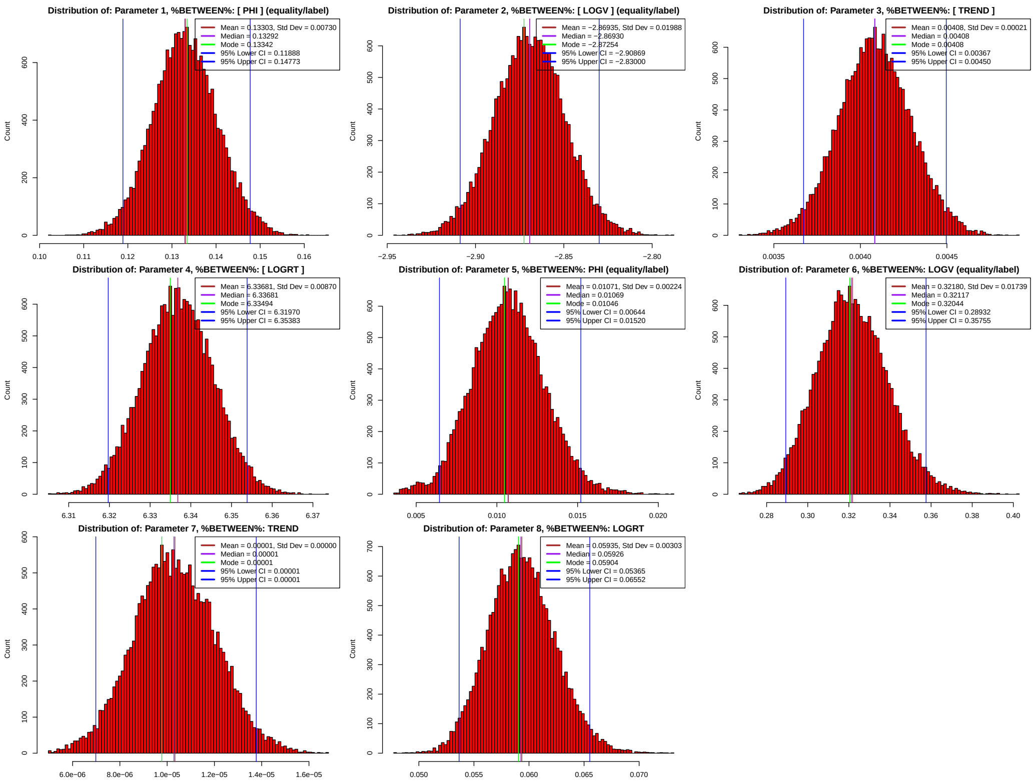

Figure SD5. Bayesian distribution for Block 2 parameters

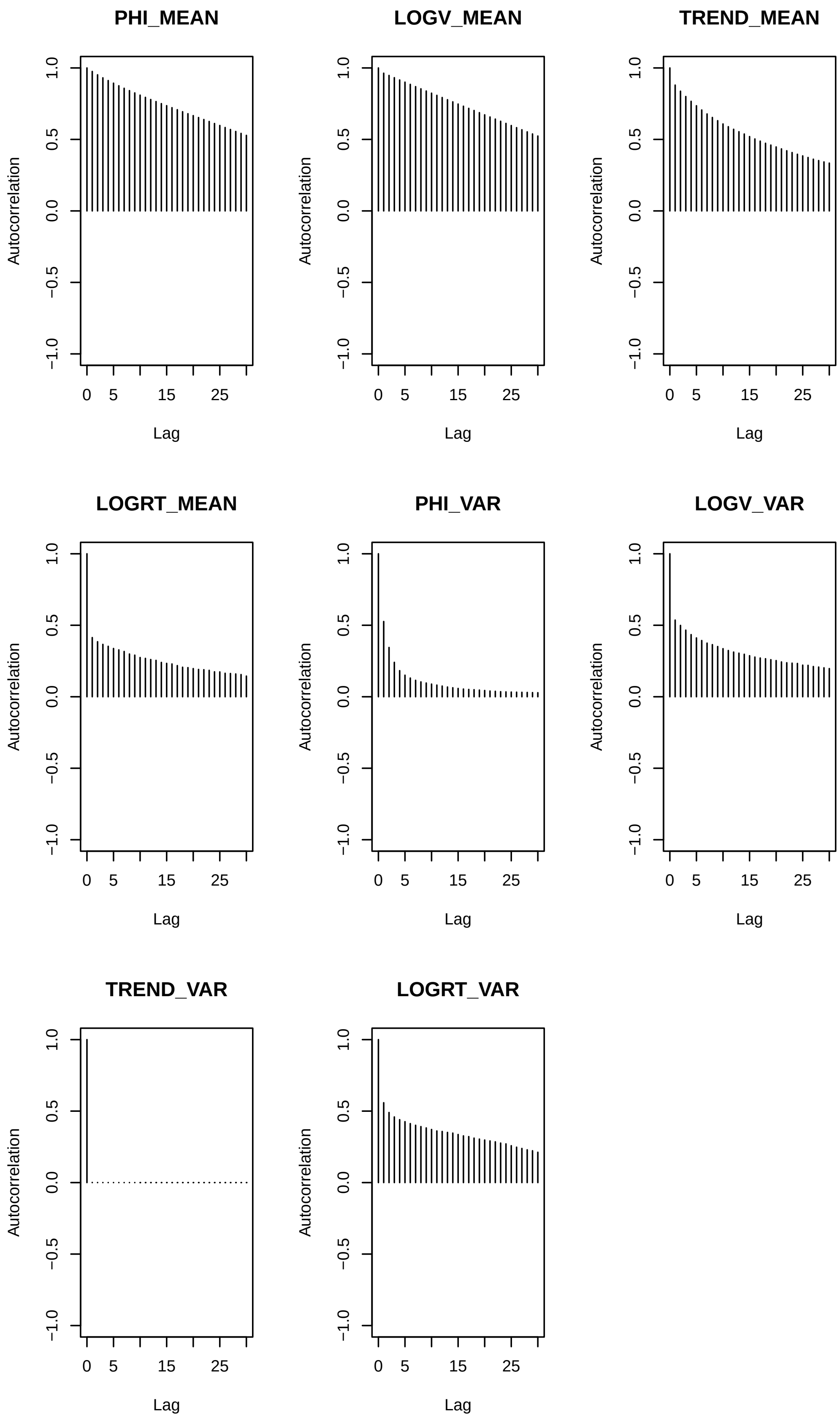

Figure SD6. Autoregression plot for Block 2 parameters

Table 3. Block 3 relative bias

	Parameters	Initial Estimates	Estimates After 2x Iterations	Relative Bias
Means	LOGRT	6.467	6.467	0.0000000
Means	PHI	0.044	0.044	0.0000000
Means	LOGV	-2.721	-2.720	0.0367512
Means	TREND	-0.001	-0.001	0.0000000
Variances	LOGRT	0.062	0.062	0.0000000
Variances	PHI	0.015	0.015	0.0000000
Variances	LOGV	0.276	0.275	0.3623188
Variances	TREND	0.000	0.000	NaN

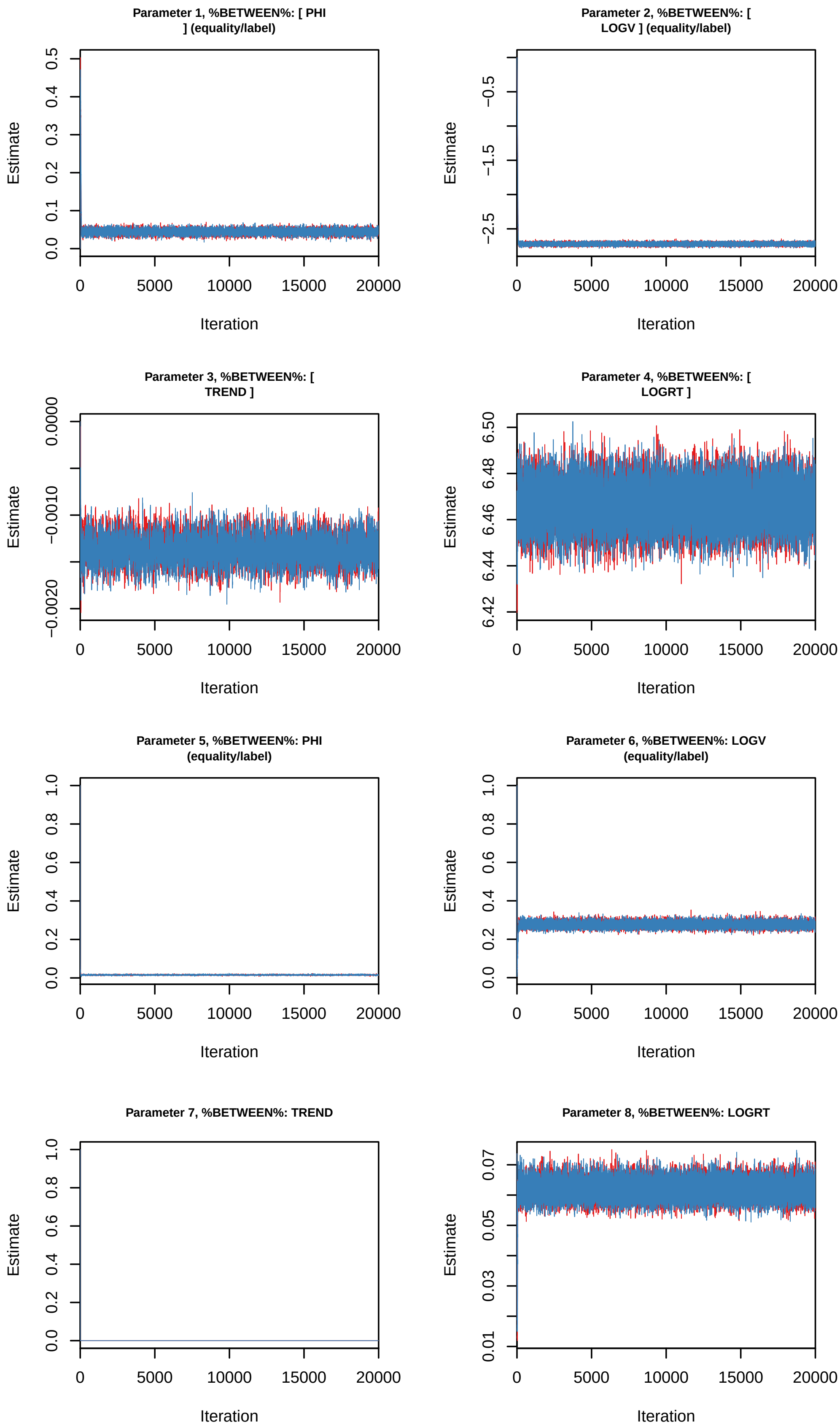

Figure SD7. Traceplots for Block 3 parameters

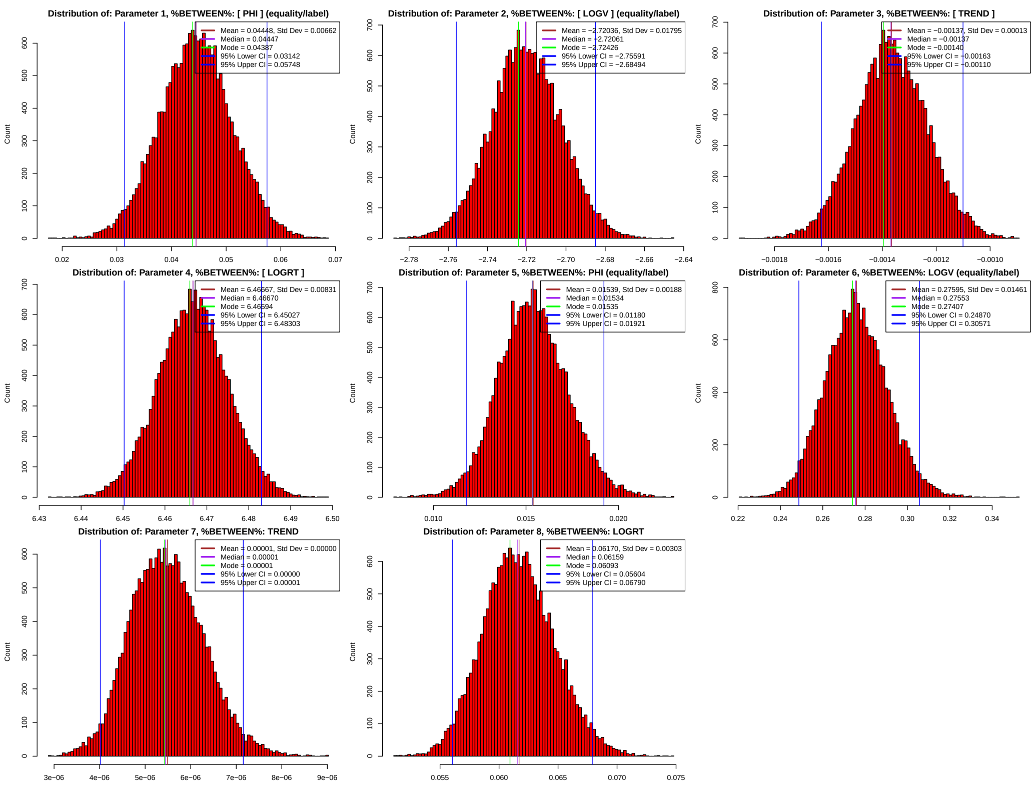

Figure SD8. Bayesian distribution for Block 3 parameters

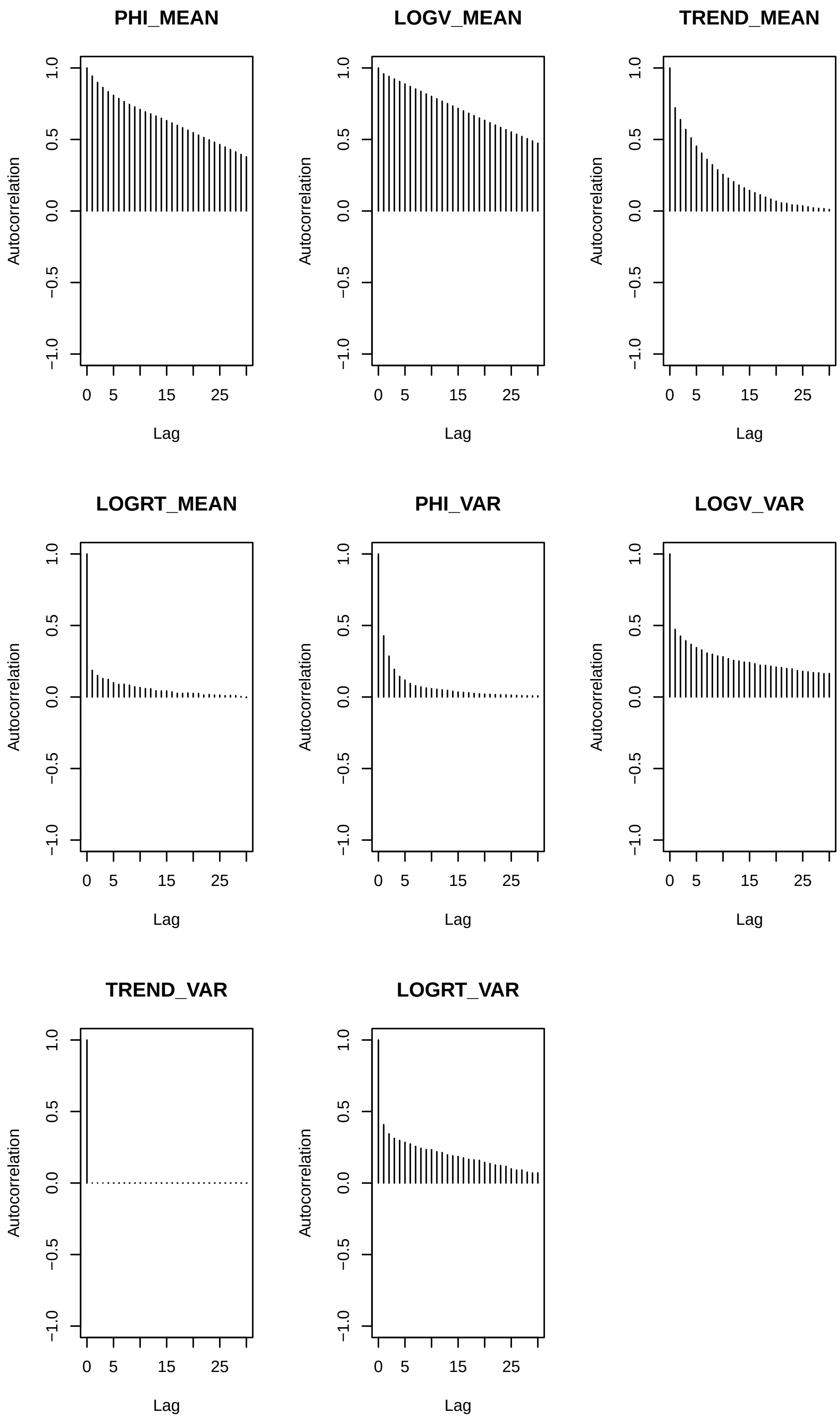

Figure SD9. Autoregression plot for Block 3 parameters

Table 4. Block 4 relative bias

	Parameters	Initial Estimates	Estimates After 2x Iterations	Relative Bias
Means	LOGRT	6.315	6.314	0.0158353
Means	PHI	0.150	0.150	0.0000000
Means	LOGV	-2.686	-2.686	0.0000000
Means	TREND	0.009	0.009	0.0000000
Variances	LOGRT	0.063	0.063	0.0000000
Variances	PHI	0.012	0.012	0.0000000
Variances	LOGV	0.300	0.299	0.3333333
Variances	TREND	0.000	0.000	NaN

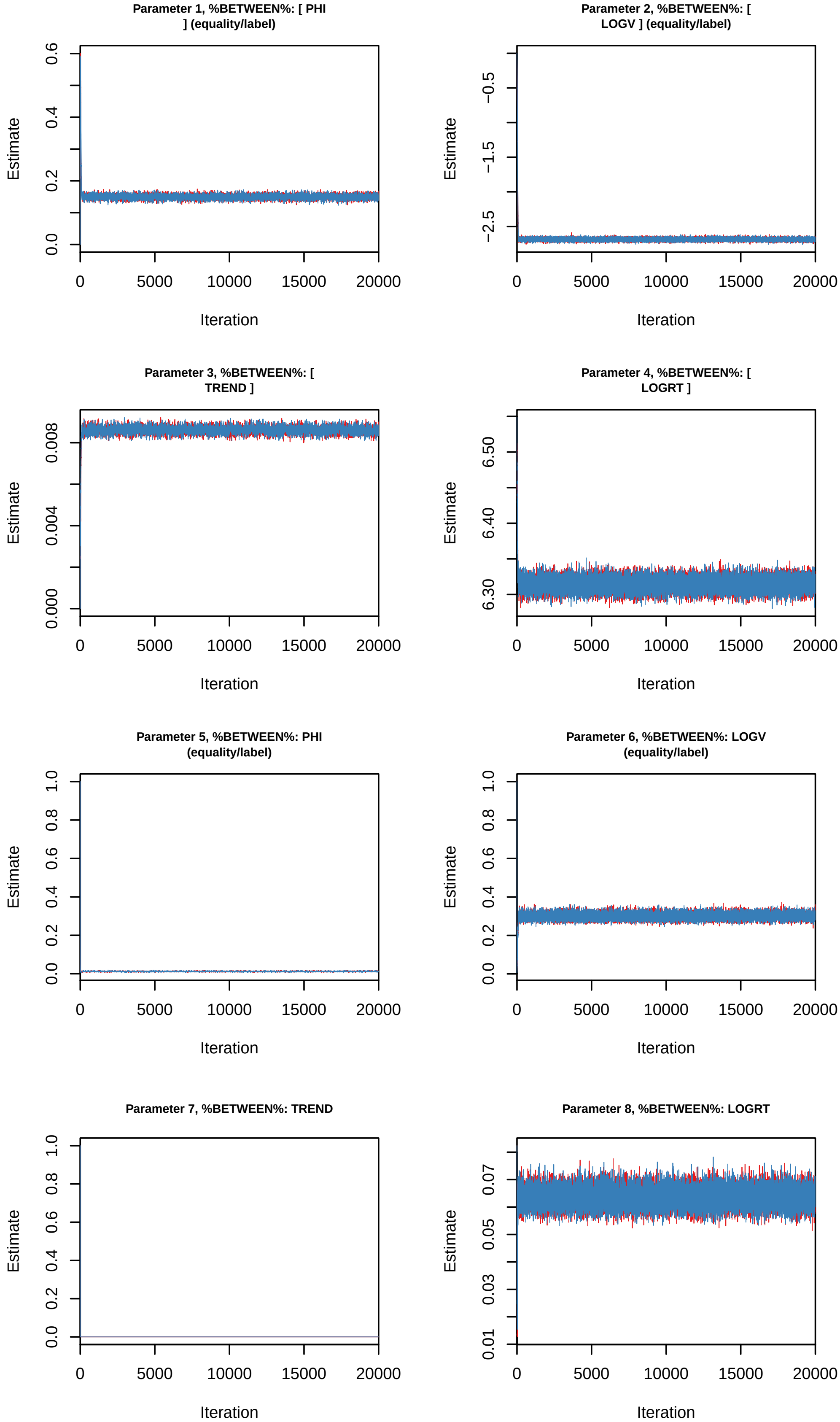

Figure SD10. Traceplots for Block 4 parameters

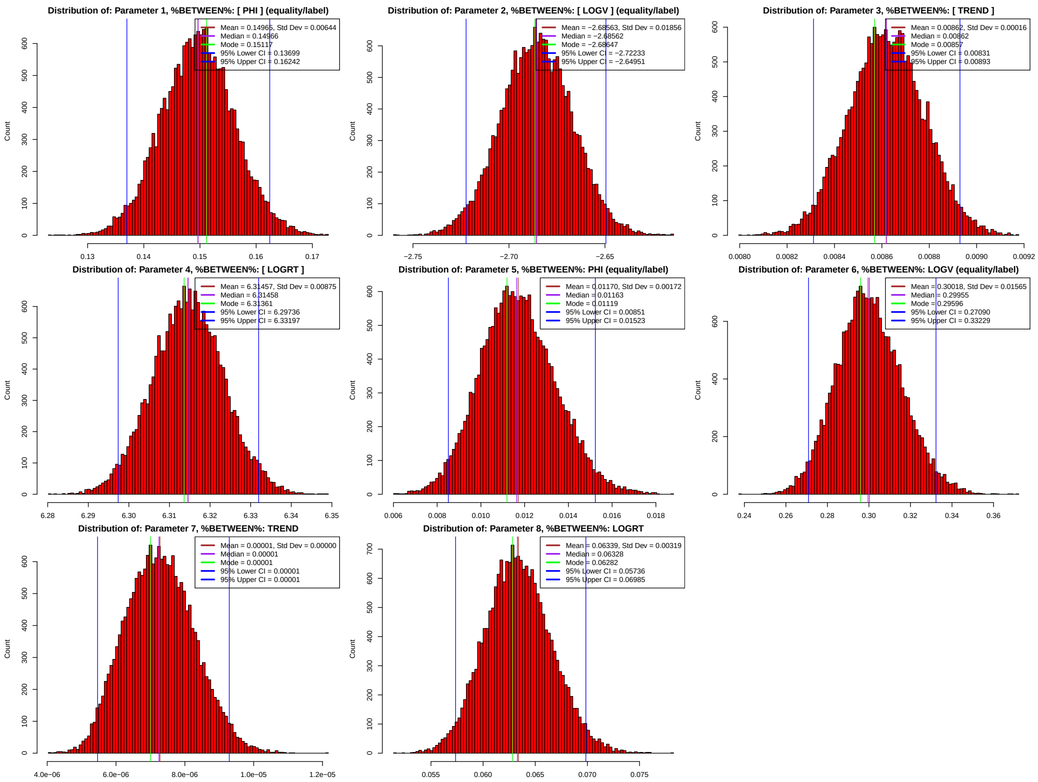

Figure SD11. Bayesian distribution for Block 4 parameters

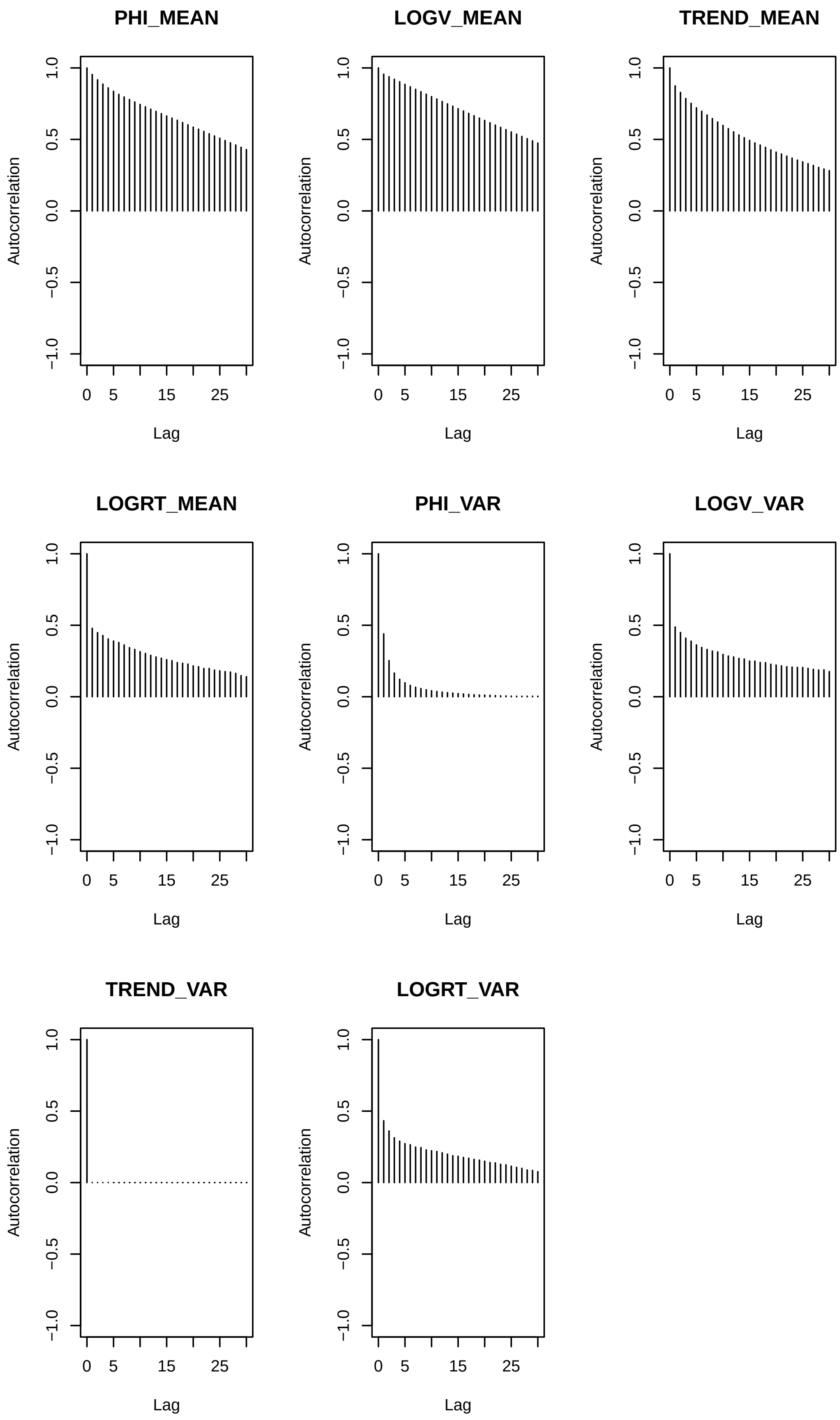

Figure SD12. Autoregression plot for Block 4 parameters

Table 5. Block 7A relative bias

	Parameters	Initial Estimates	Estimates After 2x Iterations	Relative Bias
Means	LOGRT	6.505	6.505	0.0000000
Means	PHI	0.150	0.150	0.0000000
Means	LOGV	-2.522	-2.522	0.0000000
Means	TREND	0.004	0.004	0.0000000
Variances	LOGRT	0.081	0.081	0.0000000
Variances	PHI	0.007	0.007	0.0000000
Variances	LOGV	0.534	0.536	-0.3745318
Variances	TREND	0.000	0.000	NaN

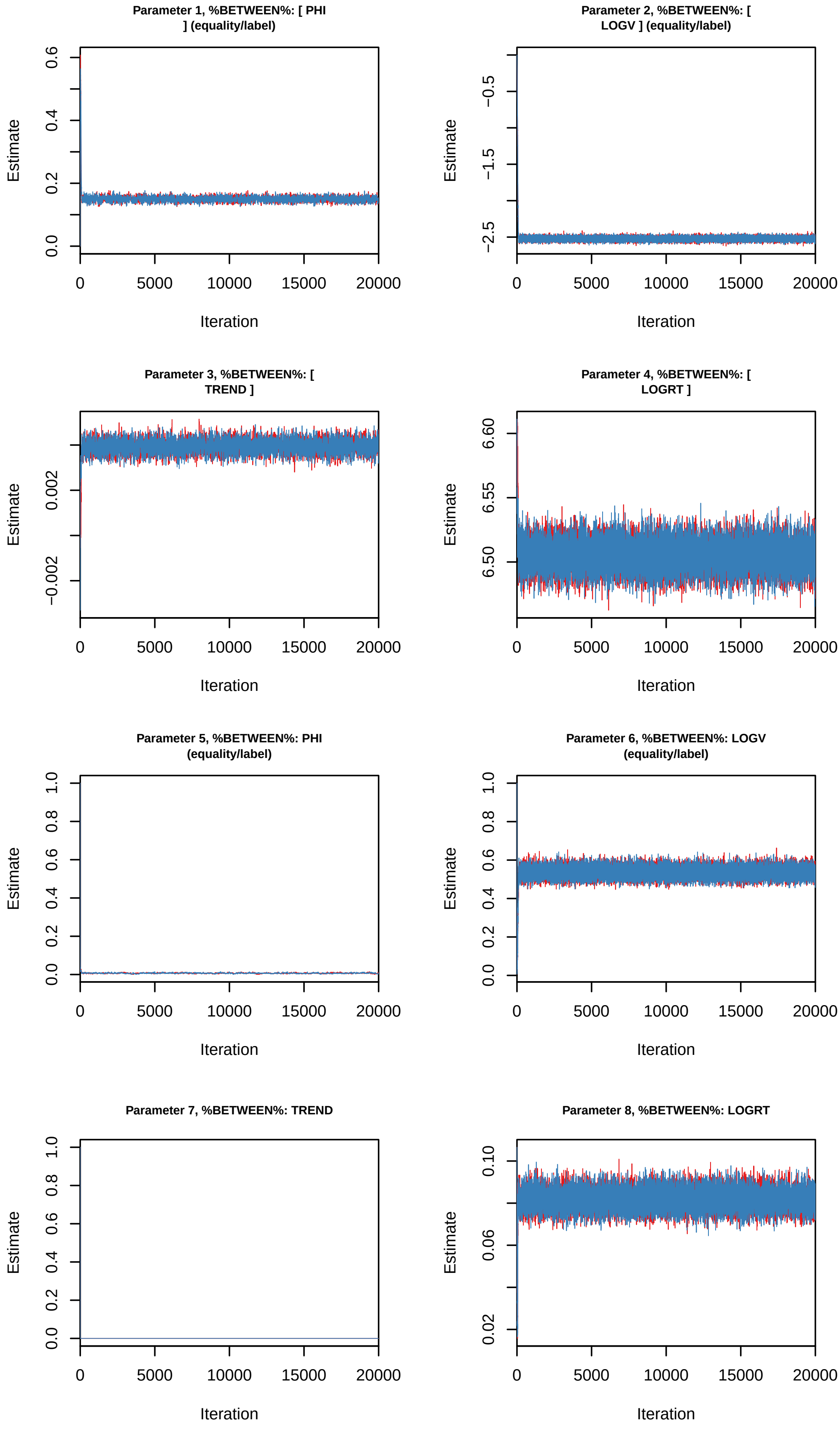

Figure SD13. Traceplots for Block 7A parameters

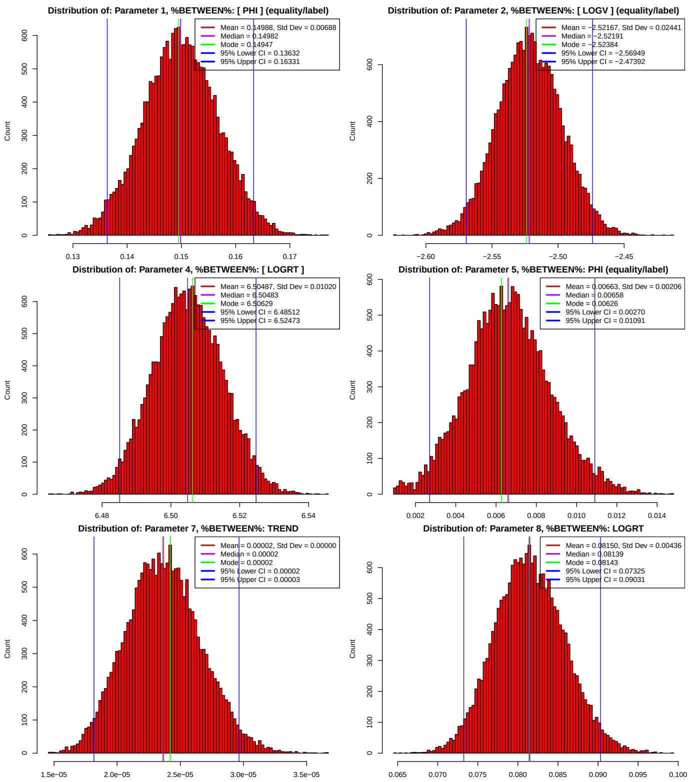

Figure SD14. Bayesian distribution for Block 7A parameters

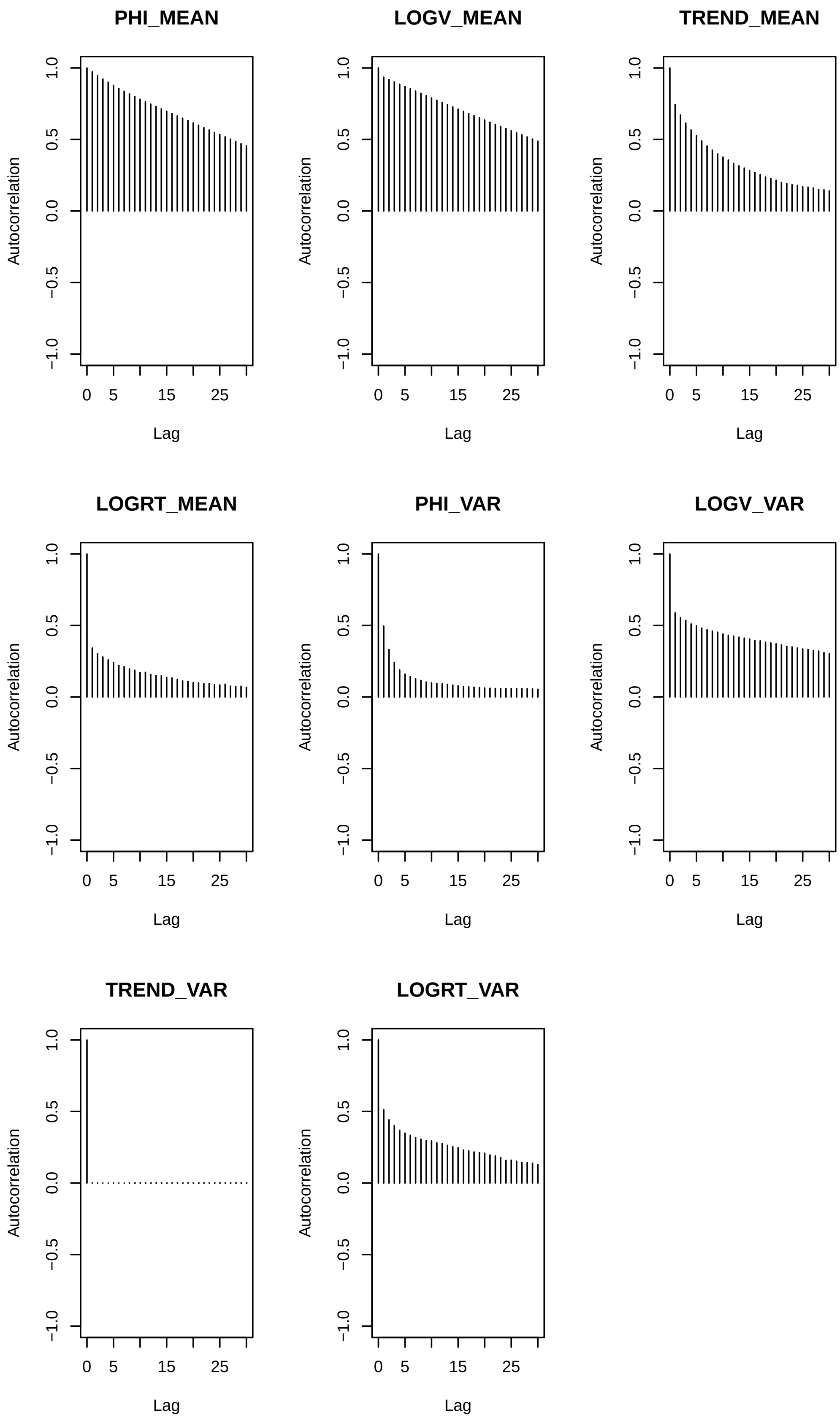

Figure SD15. Autoregression plot for Block 7A parameters

Table 6. Block 7B relative bias

	Parameters	Initial Estimates	Estimates After 2x Iterations	Relative Bias
Means	LOGRT	6.458	6.457	0.0154847
Means	PHI	0.119	0.119	0.0000000
Means	LOGV	-2.550	-2.549	0.0392157
Means	TREND	0.006	0.006	0.0000000
Variances	LOGRT	0.075	0.075	0.0000000
Variances	PHI	0.011	0.011	0.0000000
Variances	LOGV	0.807	0.807	0.0000000
Variances	TREND	0.000	0.000	NaN

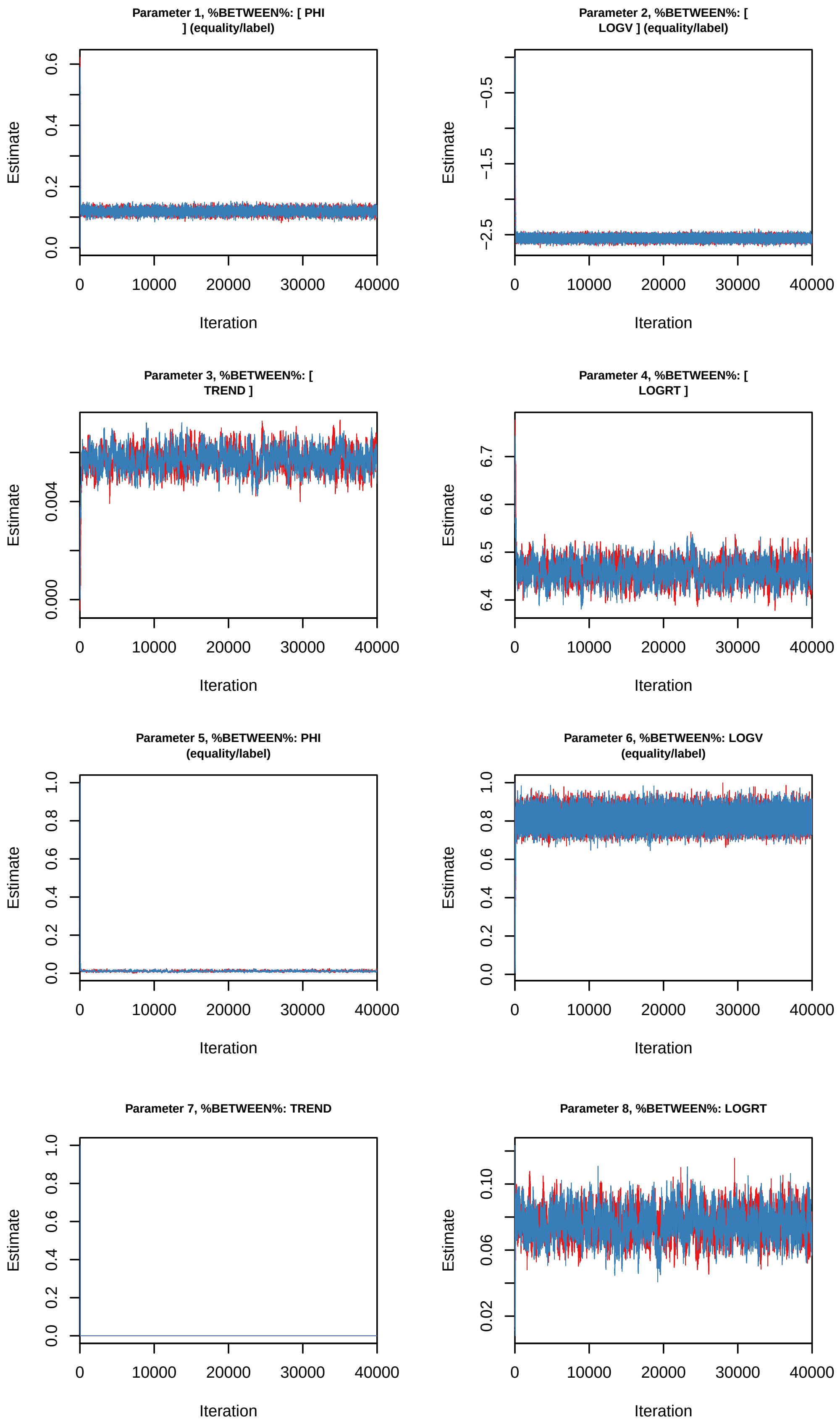

Figure SD16. Traceplots for Block 7B parameters

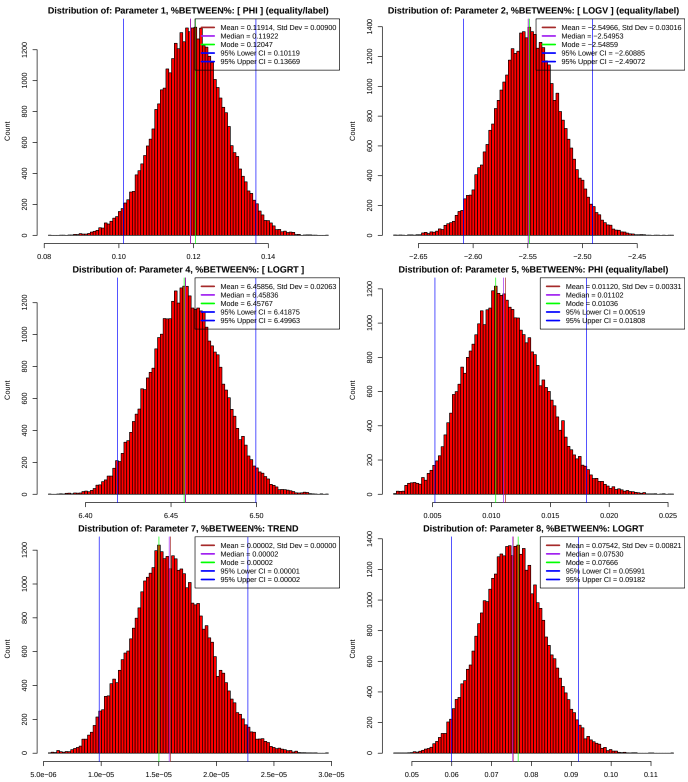

Figure SD17. Bayesian distribution for Block 7B parameters

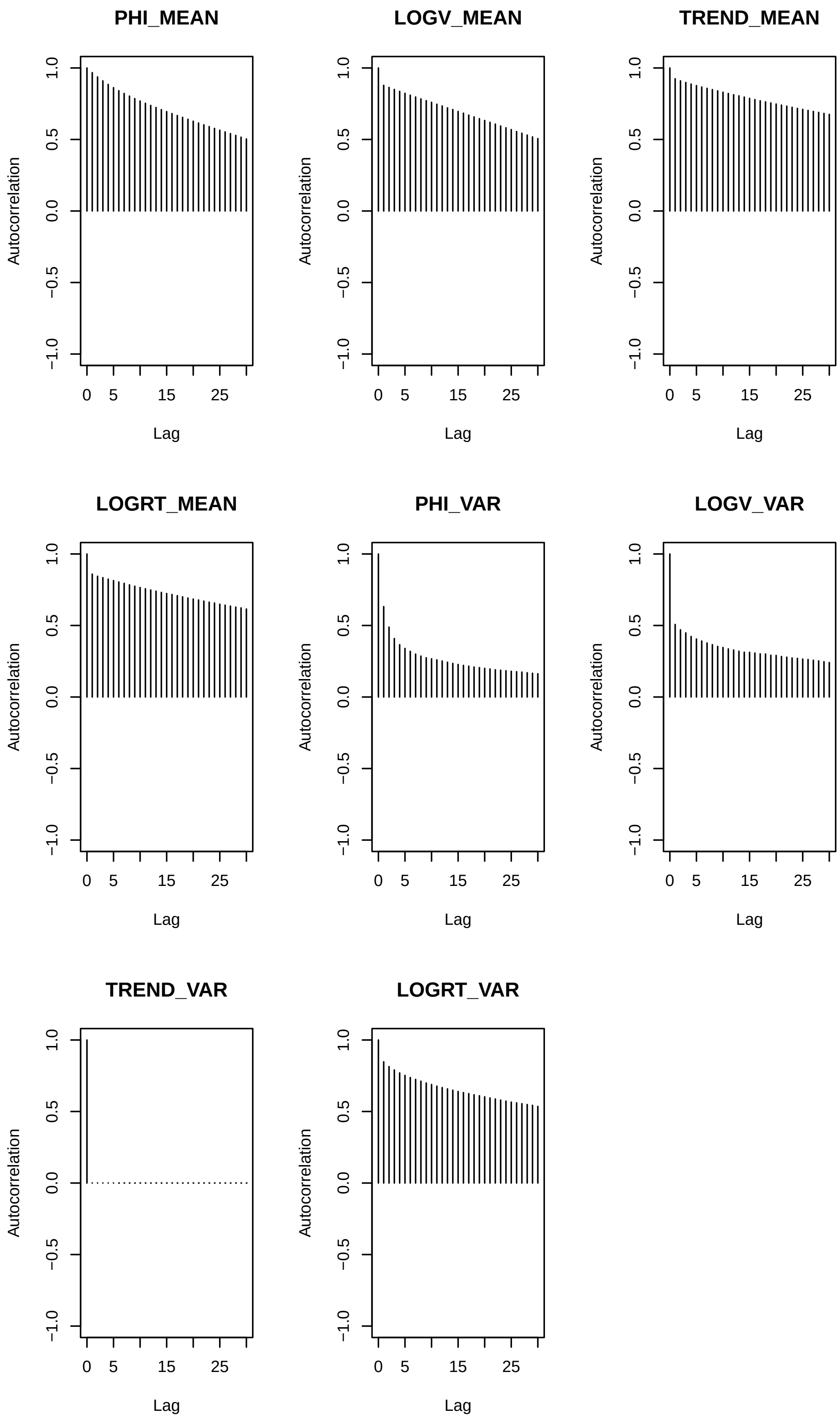

Figure SD18. Autoregression plot for Block 7B parameters

Supplement E: DSEM parameters per block

Table 7. Standardized values for between-subject parameters from DSEM in block 1

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	23.993	0.918	<.001	22.196	25.799
Means	PHI	1.329	0.124	<.001	1.137	1.624
Means	LOGV	-2.347	0.065	<.001	-2.476	-2.220
Means	TREND	-0.914	0.103	<.001	-1.137	-0.733
Variances	LOGRT	1.000	0.000	<.001	1.000	1.000
Variances	PHI	1.000	0.000	<.001	1.000	1.000
Variances	LOGV	1.000	0.000	<.001	1.000	1.000
Variances	TREND	1.000	0.000	<.001	1.000	1.000

Table 8. Unstandardized values for between-subject parameters from DSEM in block 1

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	5.967	0.011	<.001	5.946	5.988
Means	PHI	0.230	0.010	<.001	0.209	0.250
Means	LOGV	-2.731	0.038	<.001	-2.806	-2.656
Means	TREND	-0.005	0.000	<.001	-0.006	-0.005
Variances	LOGRT	0.062	0.005	<.001	0.053	0.072
Variances	PHI	0.030	0.005	<.001	0.020	0.039
Variances	LOGV	1.354	0.065	<.001	1.234	1.491
Variances	TREND	0.000	0.000	<.001	0.000	0.000

Table 9. Standardized values for between-subject parameters from DSEM in block 2

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	26.031	0.664	<.001	24.756	27.356
Means	PHI	1.292	0.165	<.001	1.036	1.686
Means	LOGV	-5.062	0.141	<.001	-5.343	-4.789
Means	TREND	1.273	0.122	<.001	1.074	1.559
Variances	LOGRT	1.000	0.000	<.001	1.000	1.000
Variances	PHI	1.000	0.000	<.001	1.000	1.000
Variances	LOGV	1.000	0.000	<.001	1.000	1.000
Variances	TREND	1.000	0.000	<.001	1.000	1.000

Table 10. Unstandardized values for between-subject parameters from DSEM in block 2

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	6.337	0.009	<.001	6.320	6.354
Means	PHI	0.133	0.007	<.001	0.119	0.148
Means	LOGV	-2.869	0.020	<.001	-2.909	-2.830
Means	TREND	0.004	0.000	<.001	0.004	0.004
Variances	LOGRT	0.059	0.003	<.001	0.054	0.066
Variances	PHI	0.011	0.002	<.001	0.006	0.015
Variances	LOGV	0.321	0.017	<.001	0.289	0.358
Variances	TREND	0.000	0.000	<.001	0.000	0.000

Table 11. Standardized values for between-subject parameters from DSEM in block 3

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	26.059	0.639	<.001	24.814	27.321
Means	PHI	0.359	0.059	<.001	0.248	0.481
Means	LOGV	-5.182	0.141	<.001	-5.465	-4.911
Means	TREND	-0.585	0.076	<.001	-0.743	-0.447
Variances	LOGRT	1.000	0.000	<.001	1.000	1.000
Variances	PHI	1.000	0.000	<.001	1.000	1.000
Variances	LOGV	1.000	0.000	<.001	1.000	1.000
Variances	TREND	1.000	0.000	<.001	1.000	1.000

Table 12. Unstandardized values for between-subject parameters from DSEM in block 3

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	6.467	0.008	<.001	6.450	6.483
Means	PHI	0.044	0.007	<.001	0.031	0.057
Means	LOGV	-2.721	0.018	<.001	-2.756	-2.685
Means	TREND	-0.001	0.000	<.001	-0.002	-0.001
Variances	LOGRT	0.062	0.003	<.001	0.056	0.068
Variances	PHI	0.015	0.002	<.001	0.012	0.019
Variances	LOGV	0.276	0.015	<.001	0.249	0.306
Variances	TREND	0.000	0.000	<.001	0.000	0.000

Table 13. Standardized values for between-subject parameters from DSEM in block 4

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	25.102	0.631	<.001	23.892	26.364
Means	PHI	1.387	0.122	<.001	1.177	1.654
Means	LOGV	-4.908	0.132	<.001	-5.166	-4.651
Means	TREND	3.201	0.221	<.001	2.831	3.681
Variances	LOGRT	1.000	0.000	<.001	1.000	1.000
Variances	PHI	1.000	0.000	<.001	1.000	1.000
Variances	LOGV	1.000	0.000	<.001	1.000	1.000
Variances	TREND	1.000	0.000	<.001	1.000	1.000

Table 14. Unstandardized values for between-subject parameters from DSEM in block 4

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	6.315	0.009	<.001	6.297	6.332
Means	PHI	0.150	0.006	<.001	0.137	0.162
Means	LOGV	-2.686	0.019	<.001	-2.722	-2.650
Means	TREND	0.009	0.000	<.001	0.008	0.009
Variances	LOGRT	0.063	0.003	<.001	0.057	0.070
Variances	PHI	0.012	0.002	<.001	0.009	0.015
Variances	LOGV	0.300	0.016	<.001	0.271	0.332
Variances	TREND	0.000	0.000	<.001	0.000	0.000

Table 15. Standardized values for between-subject parameters from DSEM in block 7A

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	22.801	0.609	<.001	21.647	24.027
Means	PHI	1.850	0.408	<.001	1.395	2.906
Means	LOGV	-3.450	0.092	<.001	-3.633	-3.275
Means	TREND	0.814	0.068	<.001	0.688	0.954
Variances	LOGRT	1.000	0.000	<.001	1.000	1.000
Variances	PHI	1.000	0.000	<.001	1.000	1.000
Variances	LOGV	1.000	0.000	<.001	1.000	1.000
Variances	TREND	1.000	0.000	<.001	1.000	1.000

Table 16. Unstandardized values for between-subject parameters from DSEM in block 7A

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	6.505	0.010	<.001	6.485	6.525
Means	PHI	0.150	0.007	<.001	0.136	0.163
Means	LOGV	-2.522	0.024	<.001	-2.569	-2.474
Means	TREND	0.004	0.000	<.001	0.003	0.004
Variances	LOGRT	0.081	0.004	<.001	0.073	0.090
Variances	PHI	0.007	0.002	<.001	0.003	0.011
Variances	LOGV	0.534	0.027	<.001	0.485	0.589
Variances	TREND	0.000	0.000	<.001	0.000	0.000

Table 17. Standardized values for between-subject parameters from DSEM in block 7B

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	23.541	1.273	<.001	21.369	26.320
Means	PHI	1.135	0.217	<.001	0.841	1.680
Means	LOGV	-2.838	0.078	<.001	-2.993	-2.687
Means	TREND	1.430	0.144	<.001	1.205	1.773
Variances	LOGRT	1.000	0.000	<.001	1.000	1.000
Variances	PHI	1.000	0.000	<.001	1.000	1.000
Variances	LOGV	1.000	0.000	<.001	1.000	1.000
Variances	TREND	1.000	0.000	<.001	1.000	1.000

Table 18. Unstandardized values for between-subject parameters from DSEM in block 7B

	Parameter	Estimate	Posterior SD	p	2.5 CI	97.5 CI
Means	LOGRT	6.458	0.021	<.001	6.419	6.500
Means	PHI	0.119	0.009	<.001	0.101	0.137
Means	LOGV	-2.550	0.030	<.001	-2.609	-2.491
Means	TREND	0.006	0.000	<.001	0.005	0.007
Variances	LOGRT	0.075	0.008	<.001	0.060	0.092
Variances	PHI	0.011	0.003	<.001	0.005	0.018
Variances	LOGV	0.807	0.041	<.001	0.732	0.891
Variances	TREND	0.000	0.000	<.001	0.000	0.000

Supplement F: Model comparison results

Table 19. Block 1 model comparison results

Model	DIC	dDIC	DICstability	pD
Full DSEM	5530.661	-	7.906	2616.835
LOGV variance = 0	15847.945	-10317.284	-4.160	1369.983
PHI variance = 0	5304.316	226.345	-3.834	2366.957
PHI = 0	5204.561	326.1	0.506	2458.861
LOGRT variance = 0	7037.575	-1506.914	-1.441	2477.667

[a] Note: dDIC shows DIC difference between Full DSEM and constrained model
[b] DICstability shows stability of the DIC under a different seed

Table 20. Block 2 model comparison results

Model	DIC	dDIC	DICstability	pD
Full DSEM	1257.241	-	3.248	2239.612
LOGV variance = 0	5306.657	-4049.416	20.344	1293.514
PHI variance = 0	1301.292	-44.0509999999999	9.904	2077.006
PHI = 0	1277.690	-20.4490000000001	15.682	2208.613
LOGRT variance = 0	3341.854	-2084.613	5.932	2260.726

[a] Note: dDIC shows DIC difference between Full DSEM and constrained model
[b] DICstability shows stability of the DIC under a different seed

Table 21. Block 3 model comparison results

Model	DIC	dDIC	DICstability	pD
Full DSEM	7344.543	-	-0.947	2494.404
LOGV variance = 0	11937.060	-4592.517	-9.094	1569.460
PHI variance = 0	7495.365	-150.822	-6.325	2189.943
PHI = 0	7427.000	-82.4570000000003	-5.619	2238.343
LOGRT variance = 0	10251.834	-2907.291	1.322	2414.749

[a] Note: dDIC shows DIC difference between Full DSEM and constrained model
[b] DICstability shows stability of the DIC under a different seed

Table 22. Block 4 model comparison results

Model	DIC	dDIC	DICstability	pD
Full DSEM	8652.236	-	-5.051	2423.513
LOGV variance = 0	13768.675	-5116.439	-7.581	1470.993
PHI variance = 0	8754.333	-102.097	5.813	2186.995
PHI = 0	8968.592	-316.356	0.404	2338.148
LOGRT variance = 0	11346.463	-2694.227	9.136	2342.108

[a] Note: dDIC shows DIC difference between Full DSEM and constrained model
[b] DICstability shows stability of the DIC under a different seed

Table 23. Block 7A model comparison results

Model	DIC	dDIC	DICstability	pD
Full DSEM	12239.46	-	6.618	2358.568
LOGV variance = 0	19463.86	-7224.405	-6.662	1392.836
PHI variance = 0	12256.87	-17.4139999999989	5.021	2252.304
PHI = 0	12296.95	-57.4899999999998	8.094	2375.933
LOGRT variance = 0	14279.90	-2040.44	4.620	2275.563

[a] Note: dDIC shows DIC difference between Full DSEM and constrained model
[b] DICstability shows stability of the DIC under a different seed

Table 24. Block 7B model comparison results

Model	DIC	dDIC	DICstability	pD
Full DSEM	8056.043	-	-4.163	2080.046
LOGV variance = 0	15232.927	-7176.884	5.088	1111.639
PHI variance = 0	8063.700	-7.65700000000015	1.026	1965.661
PHI = 0	7960.690	95.3530000000001	-3.304	2003.595
LOGRT variance = 0	8227.340	-171.297	-7.117	2030.131

[a] Note: dDIC shows DIC difference between Full DSEM and constrained model
[b] DICstability shows stability of the DIC under a different seed

Supplement G: Association between SDQ domains and DSEM parameters

Table 25. Standardized values for association between differences in SDQ domains and differences in DSEM parameters for block 1

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.152	0.055	0.003	-0.258	-0.044
PHI.ON	EMOTEACH	0.055	0.060	0.178	-0.061	0.174
PHI.ON	CONTEACH	-0.033	0.071	0.318	-0.174	0.104
PHI.ON	HYPTEACH	0.052	0.065	0.209	-0.075	0.181
PHI.ON	PEERTEACH	-0.048	0.067	0.242	-0.177	0.085
PHI.ON	PROTEACH	0.016	0.068	0.408	-0.118	0.147
LOGV.ON	AGE	-0.163	0.032	<.001	-0.225	-0.100
LOGV.ON	EMOTEACH	-0.052	0.037	0.08	-0.123	0.020
LOGV.ON	CONTEACH	0.002	0.042	0.483	-0.081	0.085
LOGV.ON	HYPTEACH	0.128	0.039	0.001	0.050	0.205
LOGV.ON	PEERTEACH	0.058	0.041	0.077	-0.023	0.137
LOGV.ON	PROTEACH	-0.056	0.041	0.087	-0.136	0.024
TREND.ON	AGE	-0.127	0.071	0.038	-0.262	0.014
TREND.ON	EMOTEACH	-0.002	0.082	0.493	-0.159	0.160
TREND.ON	CONTEACH	0.132	0.099	0.095	-0.066	0.323
TREND.ON	HYPTEACH	-0.054	0.089	0.276	-0.227	0.122
TREND.ON	PEERTEACH	0.148	0.093	0.056	-0.035	0.330
TREND.ON	PROTEACH	0.290	0.089	0.001	0.112	0.458
LOGRT.ON	AGE	-0.470	0.036	<.001	-0.538	-0.398
LOGRT.ON	EMOTEACH	0.071	0.046	0.063	-0.020	0.160
LOGRT.ON	CONTEACH	-0.074	0.054	0.085	-0.181	0.032
LOGRT.ON	HYPTEACH	0.050	0.050	0.162	-0.049	0.147
LOGRT.ON	PEERTEACH	-0.039	0.052	0.225	-0.141	0.062
LOGRT.ON	PROTEACH	-0.169	0.051	0.001	-0.266	-0.068

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend
[c] EMOTEACH = Emotion problems, CONTEACH = Conduct problems
[d] HYPTEACH = ADHD, PEERTEACH = Peer relations, PROTEACH = Prosociality

Table 26. Standardized values for association between differences in SDQ domains and differences in DSEM parameters for block 2

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	0.043	0.067	0.266	-0.090	0.174
PHI.ON	EMOTEACH	0.193	0.077	0.005	0.045	0.349
PHI.ON	CONTEACH	0.033	0.088	0.355	-0.140	0.206
PHI.ON	HYPTEACH	0.043	0.082	0.299	-0.116	0.205
PHI.ON	PEERTEACH	-0.107	0.084	0.103	-0.271	0.057
PHI.ON	PROTEACH	-0.043	0.086	0.305	-0.211	0.127
PHI.ON	ERRORB2	0.162	0.071	0.009	0.026	0.303
LOGV.ON	AGE	-0.243	0.031	<.001	-0.302	-0.182
LOGV.ON	EMOTEACH	0.007	0.035	0.426	-0.062	0.075
LOGV.ON	CONTEACH	0.043	0.040	0.144	-0.036	0.121
LOGV.ON	HYPTEACH	0.146	0.037	<.001	0.073	0.219
LOGV.ON	PEERTEACH	0.049	0.039	0.104	-0.027	0.126
LOGV.ON	PROTEACH	0.020	0.039	0.307	-0.058	0.096
LOGV.ON	ERRORB2	0.398	0.028	<.001	0.342	0.453
TREND.ON	EMOTEACH	-0.023	0.078	0.382	-0.177	0.128
TREND.ON	CONTEACH	0.107	0.092	0.119	-0.073	0.290
TREND.ON	HYPTEACH	-0.004	0.083	0.482	-0.169	0.160
TREND.ON	PEERTEACH	0.001	0.085	0.497	-0.166	0.165
TREND.ON	PROTEACH	0.022	0.084	0.399	-0.143	0.185
TREND.ON	AGE	0.011	0.067	0.433	-0.121	0.143
TREND.ON	ERRORB2	-0.039	0.083	0.319	-0.202	0.124
LOGRT.ON	AGE	-0.606	0.024	<.001	-0.652	-0.558
LOGRT.ON	EMOTEACH	0.081	0.032	0.006	0.017	0.145
LOGRT.ON	CONTEACH	-0.028	0.038	0.227	-0.103	0.046
LOGRT.ON	HYPTEACH	0.073	0.035	0.018	0.004	0.141
LOGRT.ON	PEERTEACH	0.058	0.036	0.051	-0.012	0.129
LOGRT.ON	PROTEACH	-0.011	0.036	0.376	-0.082	0.058
LOGRT.ON	ERRORB2	-0.444	0.030	<.001	-0.502	-0.384

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend
[c] EMOTEACH = Emotion problems, CONTEACH = Conduct problems
[d] HYPTEACH = ADHD, PEERTEACH = Peer relations, PROTEACH = Prosociality

Table 27. Standardized values for association between differences in SDQ domains and differences in DSEM parameters for block 3

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	0.032	0.052	0.268	-0.071	0.133
PHI.ON	EMOTEACH	0.108	0.058	0.032	-0.006	0.223
PHI.ON	CONTEACH	0.111	0.068	0.05	-0.020	0.245
PHI.ON	HYPTEACH	0.010	0.064	0.438	-0.116	0.137
PHI.ON	PEERTEACH	-0.075	0.065	0.125	-0.202	0.053
PHI.ON	PROTEACH	-0.063	0.065	0.168	-0.191	0.065
PHI.ON	ERRORB3	0.014	0.052	0.398	-0.089	0.114
LOGV.ON	AGE	-0.337	0.030	<.001	-0.395	-0.277
LOGV.ON	EMOTEACH	0.047	0.035	0.093	-0.023	0.117
LOGV.ON	CONTEACH	0.028	0.041	0.245	-0.051	0.107
LOGV.ON	HYPTEACH	0.204	0.037	<.001	0.129	0.276
LOGV.ON	PEERTEACH	0.009	0.039	0.409	-0.068	0.085
LOGV.ON	PROTEACH	0.042	0.040	0.145	-0.036	0.120
LOGV.ON	ERRORB3	0.225	0.031	<.001	0.164	0.284
TREND.ON	EMOTEACH	0.005	0.069	0.469	-0.131	0.139
TREND.ON	CONTEACH	0.002	0.080	0.489	-0.154	0.158
TREND.ON	HYPTEACH	0.018	0.073	0.405	-0.124	0.161
TREND.ON	PEERTEACH	0.006	0.075	0.468	-0.137	0.155
TREND.ON	PROTEACH	-0.011	0.077	0.445	-0.163	0.140
TREND.ON	AGE	-0.151	0.058	0.005	-0.263	-0.036
TREND.ON	ERRORB3	-0.106	0.063	0.047	-0.226	0.017
LOGRT.ON	AGE	-0.584	0.023	<.001	-0.627	-0.538
LOGRT.ON	EMOTEACH	0.081	0.030	0.004	0.020	0.140
LOGRT.ON	CONTEACH	0.019	0.035	0.296	-0.050	0.089
LOGRT.ON	HYPTEACH	0.071	0.033	0.015	0.007	0.136
LOGRT.ON	PEERTEACH	0.054	0.034	0.057	-0.013	0.118
LOGRT.ON	PROTEACH	0.022	0.034	0.264	-0.046	0.088
LOGRT.ON	ERRORB3	-0.400	0.026	<.001	-0.451	-0.348

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend
[c] EMOTEACH = Emotion problems, CONTEACH = Conduct problems
[d] HYPTEACH = ADHD, PEERTEACH = Peer relations, PROTEACH = Prosociality

Table 28. Standardized values for association between differences in SDQ domains and differences in DSEM parameters for block 4

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.104	0.058	0.037	-0.214	0.009
PHI.ON	EMOTEACH	-0.096	0.066	0.073	-0.225	0.033
PHI.ON	CONTEACH	-0.050	0.076	0.256	-0.199	0.098
PHI.ON	HYPTEACH	0.139	0.071	0.024	0.001	0.279
PHI.ON	PEERTEACH	0.134	0.073	0.031	-0.007	0.277
PHI.ON	PROTEACH	0.073	0.074	0.162	-0.072	0.220
PHI.ON	ERROR4COM	0.027	0.064	0.334	-0.099	0.153
PHI.ON	ERROR4INC	0.039	0.065	0.275	-0.088	0.168
LOGV.ON	AGE	-0.295	0.030	<.001	-0.353	-0.235
LOGV.ON	EMOTEACH	0.031	0.036	0.196	-0.039	0.100
LOGV.ON	CONTEACH	0.010	0.041	0.399	-0.070	0.090
LOGV.ON	HYPTEACH	0.229	0.038	<.001	0.154	0.303
LOGV.ON	PEERTEACH	0.016	0.040	0.338	-0.062	0.094
LOGV.ON	PROTEACH	0.024	0.040	0.276	-0.054	0.102
LOGV.ON	ERROR4COM	0.058	0.035	0.047	-0.009	0.126
LOGV.ON	ERROR4INC	0.222	0.034	<.001	0.154	0.288
TREND.ON	EMOTEACH	0.010	0.063	0.44	-0.114	0.131
TREND.ON	CONTEACH	0.063	0.077	0.207	-0.088	0.212
TREND.ON	HYPTEACH	0.038	0.070	0.294	-0.100	0.174
TREND.ON	PEERTEACH	-0.014	0.072	0.422	-0.156	0.126
TREND.ON	PROTEACH	0.116	0.070	0.049	-0.023	0.253
TREND.ON	AGE	-0.260	0.053	<.001	-0.363	-0.156
TREND.ON	ERROR4COM	-0.068	0.065	0.148	-0.195	0.059
TREND.ON	ERROR4INC	0.524	0.060	<.001	0.405	0.641
LOGRT.ON	AGE	-0.496	0.024	<.001	-0.541	-0.448
LOGRT.ON	EMOTEACH	0.066	0.028	0.01	0.011	0.121
LOGRT.ON	CONTEACH	-0.012	0.034	0.365	-0.078	0.054
LOGRT.ON	HYPTEACH	0.124	0.031	<.001	0.063	0.186
LOGRT.ON	PEERTEACH	0.039	0.032	0.11	-0.024	0.102
LOGRT.ON	PROTEACH	-0.012	0.032	0.357	-0.074	0.051
LOGRT.ON	ERROR4COM	-0.130	0.029	<.001	-0.186	-0.074
LOGRT.ON	ERROR4INC	-0.544	0.027	<.001	-0.595	-0.492

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend
[c] EMOTEACH = Emotion problems, CONTEACH = Conduct problems
[d] HYPTEACH = ADHD, PEERTEACH = Peer relations, PROTEACH = Prosociality

Table 29. Standardized values for association between differences in SDQ domains and differences in DSEM parameters for block 7A

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.124	0.083	0.061	-0.296	0.033
PHI.ON	EMOTEACH	0.010	0.104	0.461	-0.196	0.214
PHI.ON	CONTEACH	-0.144	0.111	0.091	-0.368	0.067
PHI.ON	HYPTEACH	0.130	0.107	0.099	-0.069	0.354
PHI.ON	PEERTEACH	-0.022	0.104	0.417	-0.223	0.182
PHI.ON	PROTEACH	-0.102	0.100	0.148	-0.302	0.088
PHI.ON	ERRORB71	0.185	0.087	0.01	0.029	0.367
LOGV.ON	AGE	-0.316	0.029	<.001	-0.372	-0.258
LOGV.ON	EMOTEACH	-0.045	0.039	0.123	-0.121	0.031
LOGV.ON	CONTEACH	0.105	0.040	0.004	0.026	0.183
LOGV.ON	HYPTEACH	0.215	0.039	<.001	0.138	0.289
LOGV.ON	PEERTEACH	0.056	0.039	0.076	-0.021	0.133
LOGV.ON	PROTEACH	0.086	0.036	0.009	0.015	0.157
LOGV.ON	ERRORB71	0.247	0.029	<.001	0.189	0.303
TREND.ON	EMOTEACH	0.058	0.070	0.209	-0.079	0.194
TREND.ON	CONTEACH	0.063	0.075	0.201	-0.084	0.209
TREND.ON	HYPTEACH	0.093	0.071	0.097	-0.047	0.229
TREND.ON	PEERTEACH	-0.054	0.070	0.221	-0.191	0.083
TREND.ON	PROTEACH	0.037	0.065	0.286	-0.092	0.163
TREND.ON	AGE	-0.173	0.057	0.001	-0.281	-0.060
TREND.ON	ERRORB71	-0.019	0.066	0.385	-0.150	0.110
LOGRT.ON	AGE	-0.565	0.027	<.001	-0.615	-0.510
LOGRT.ON	EMOTEACH	-0.047	0.041	0.125	-0.127	0.034
LOGRT.ON	CONTEACH	0.076	0.043	0.039	-0.009	0.159
LOGRT.ON	HYPTEACH	0.151	0.041	<.001	0.070	0.231
LOGRT.ON	PEERTEACH	0.072	0.041	0.04	-0.009	0.153
LOGRT.ON	PROTEACH	0.067	0.038	0.041	-0.009	0.142
LOGRT.ON	ERRORB71	-0.187	0.035	<.001	-0.254	-0.117

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend
[c] EMOTEACH = Emotion problems, CONTEACH = Conduct problems
[d] HYPTEACH = ADHD, PEERTEACH = Peer relations, PROTEACH = Prosociality

Table 30. Standardized values for association between differences in SDQ domains and differences in DSEM parameters for block 7B

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.176	0.078	0.011	-0.334	-0.026
PHI.ON	EMOTEACH	-0.125	0.089	0.077	-0.304	0.047
PHI.ON	CONTEACH	0.008	0.101	0.465	-0.190	0.205
PHI.ON	HYPTEACH	0.154	0.093	0.042	-0.022	0.344
PHI.ON	PEERTEACH	0.125	0.099	0.101	-0.067	0.322
PHI.ON	PROTEACH	0.014	0.096	0.443	-0.173	0.201
PHI.ON	ERRORB72	0.163	0.086	0.029	-0.006	0.334
LOGV.ON	AGE	-0.408	0.028	<.001	-0.462	-0.352
LOGV.ON	EMOTEACH	0.047	0.033	0.081	-0.019	0.113
LOGV.ON	CONTEACH	0.062	0.038	0.055	-0.013	0.136
LOGV.ON	HYPTEACH	0.222	0.035	<.001	0.152	0.291
LOGV.ON	PEERTEACH	0.015	0.037	0.346	-0.058	0.088
LOGV.ON	PROTEACH	0.062	0.037	0.048	-0.011	0.134
LOGV.ON	ERRORB72	0.153	0.030	<.001	0.095	0.211
TREND.ON	EMOTEACH	0.032	0.101	0.377	-0.166	0.227
TREND.ON	CONTEACH	0.113	0.134	0.192	-0.155	0.372
TREND.ON	HYPTEACH	0.144	0.114	0.104	-0.083	0.366
TREND.ON	PEERTEACH	0.063	0.115	0.297	-0.169	0.283
TREND.ON	PROTEACH	0.249	0.124	0.027	-0.003	0.479
TREND.ON	AGE	-0.292	0.088	<.001	-0.463	-0.119
TREND.ON	ERRORB72	0.185	0.114	0.059	-0.041	0.399
LOGRT.ON	AGE	-0.534	0.057	<.001	-0.632	-0.409
LOGRT.ON	EMOTEACH	0.046	0.075	0.273	-0.102	0.190
LOGRT.ON	CONTEACH	-0.029	0.099	0.377	-0.222	0.168
LOGRT.ON	HYPTEACH	0.103	0.084	0.117	-0.063	0.269
LOGRT.ON	PEERTEACH	-0.017	0.086	0.423	-0.182	0.157
LOGRT.ON	PROTEACH	-0.159	0.094	0.046	-0.347	0.024
LOGRT.ON	ERRORB72	-0.350	0.083	<.001	-0.512	-0.188

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend
[c] EMOTEACH = Emotion problems, CONTEACH = Conduct problems
[d] HYPTEACH = ADHD, PEERTEACH = Peer relations, PROTEACH = Prosociality

Supplement H: Association between SWAN domains and DSEM parameters

Table 31. Standardized values for association between differences in SWAN domains and differences in DSEM parameters for block 1

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.153	0.054	0.002	-0.257	-0.048
PHI.ON	Inattention	-0.036	0.083	0.333	-0.196	0.129
PHI.ON	Hyp/Imp	0.020	0.083	0.403	-0.145	0.182
LOGV.ON	AGE	-0.153	0.031	<.001	-0.214	-0.091
LOGV.ON	Inattention	0.144	0.049	0.002	0.048	0.240
LOGV.ON	Hyp/Imp	0.041	0.050	0.208	-0.058	0.138
TREND.ON	AGE	-0.108	0.073	0.068	-0.249	0.037
TREND.ON	Inattention	0.061	0.113	0.296	-0.160	0.283
TREND.ON	Hyp/Imp	-0.116	0.116	0.158	-0.350	0.107
LOGRT.ON	AGE	-0.480	0.035	<.001	-0.546	-0.410
LOGRT.ON	Inattention	0.148	0.062	0.008	0.026	0.269
LOGRT.ON	Hyp/Imp	-0.053	0.063	0.2	-0.174	0.072

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 32. Standardized values for association between differences in SWAN domains and differences in DSEM parameters for block 2

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	0.039	0.067	0.28	-0.094	0.171
PHI.ON	ERRORB2	0.166	0.070	0.009	0.030	0.305
PHI.ON	Inattention	0.102	0.104	0.164	-0.104	0.307
PHI.ON	Hyp/Imp	-0.072	0.104	0.24	-0.279	0.131
LOGV.ON	AGE	-0.226	0.030	<.001	-0.285	-0.167
LOGV.ON	ERRORB2	0.410	0.029	<.001	0.353	0.465
LOGV.ON	Inattention	0.208	0.046	<.001	0.116	0.298
LOGV.ON	Hyp/Imp	0.001	0.047	0.494	-0.091	0.093
TREND.ON	AGE	0.021	0.068	0.375	-0.110	0.158
TREND.ON	ERRORB2	-0.028	0.081	0.368	-0.188	0.129
TREND.ON	Inattention	0.077	0.102	0.226	-0.119	0.277
TREND.ON	Hyp/Imp	0.018	0.103	0.433	-0.183	0.219
LOGRT.ON	AGE	-0.595	0.024	<.001	-0.641	-0.547
LOGRT.ON	ERRORB2	-0.441	0.029	<.001	-0.499	-0.383
LOGRT.ON	Inattention	0.216	0.042	<.001	0.133	0.298
LOGRT.ON	Hyp/Imp	-0.103	0.043	0.008	-0.187	-0.018

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 33. Standardized values for association between differences in SWAN domains and differences in DSEM parameters for block 3

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	0.031	0.052	0.272	-0.070	0.136
PHI.ON	Inattention	0.009	0.081	0.452	-0.148	0.169
PHI.ON	Hyp/Imp	0.086	0.080	0.146	-0.074	0.240
PHI.ON	ERRORB3	0.010	0.052	0.424	-0.091	0.113
LOGV.ON	AGE	-0.325	0.030	<.001	-0.382	-0.266
LOGV.ON	Inattention	0.273	0.047	<.001	0.180	0.364
LOGV.ON	Hyp/Imp	-0.045	0.047	0.173	-0.138	0.048
LOGV.ON	ERRORB3	0.229	0.030	<.001	0.169	0.287
TREND.ON	AGE	-0.153	0.058	0.005	-0.265	-0.038
TREND.ON	Inattention	0.183	0.090	0.022	0.006	0.356
TREND.ON	Hyp/Imp	-0.100	0.090	0.132	-0.277	0.075
TREND.ON	ERRORB3	-0.103	0.063	0.05	-0.227	0.021
LOGRT.ON	AGE	-0.570	0.023	<.001	-0.613	-0.526
LOGRT.ON	Inattention	0.216	0.040	<.001	0.136	0.295
LOGRT.ON	Hyp/Imp	-0.086	0.040	0.018	-0.165	-0.006
LOGRT.ON	ERRORB3	-0.400	0.026	<.001	-0.450	-0.349

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 34. Standardized values for association between differences in SWAN domains and differences in DSEM parameters for block 4

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.087	0.057	0.062	-0.200	0.025
PHI.ON	Inattention	-0.025	0.090	0.391	-0.198	0.153
PHI.ON	Hyp/Imp	0.084	0.090	0.176	-0.093	0.257
PHI.ON	ERROR4COM	0.045	0.064	0.242	-0.081	0.172
PHI.ON	ERROR4INC	0.046	0.066	0.242	-0.084	0.174
LOGV.ON	AGE	-0.282	0.030	<.001	-0.341	-0.223
LOGV.ON	Inattention	0.275	0.047	<.001	0.182	0.366
LOGV.ON	Hyp/Imp	-0.034	0.048	0.235	-0.128	0.060
LOGV.ON	ERROR4COM	0.061	0.034	0.038	-0.006	0.128
LOGV.ON	ERROR4INC	0.224	0.034	<.001	0.158	0.289
TREND.ON	AGE	-0.261	0.053	<.001	-0.363	-0.156
TREND.ON	Inattention	0.166	0.085	0.025	0.000	0.334
TREND.ON	Hyp/Imp	-0.134	0.088	0.065	-0.303	0.038
TREND.ON	ERROR4COM	-0.068	0.065	0.152	-0.195	0.061
TREND.ON	ERROR4INC	0.532	0.062	<.001	0.408	0.650
LOGRT.ON	AGE	-0.485	0.024	<.001	-0.530	-0.438
LOGRT.ON	Inattention	0.216	0.038	<.001	0.142	0.291
LOGRT.ON	Hyp/Imp	-0.038	0.038	0.162	-0.114	0.037
LOGRT.ON	ERROR4COM	-0.129	0.028	<.001	-0.184	-0.073
LOGRT.ON	ERROR4INC	-0.551	0.026	<.001	-0.602	-0.499

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 35. Standardized values for association between differences in SWAN domains and differences in DSEM parameters for block 7A

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.117	0.082	0.071	-0.282	0.040
PHI.ON	Inattention	0.034	0.132	0.397	-0.222	0.293
PHI.ON	Hyp/Imp	-0.048	0.130	0.35	-0.308	0.200
PHI.ON	ERRORB71	0.192	0.085	0.01	0.033	0.371
LOGV.ON	AGE	-0.313	0.029	<.001	-0.368	-0.256
LOGV.ON	Inattention	0.272	0.044	<.001	0.185	0.359
LOGV.ON	Hyp/Imp	0.002	0.045	0.479	-0.085	0.090
LOGV.ON	ERRORB71	0.236	0.029	<.001	0.178	0.292
TREND.ON	AGE	-0.183	0.054	0.001	-0.288	-0.077
TREND.ON	Inattention	0.037	0.083	0.325	-0.123	0.202
TREND.ON	Hyp/Imp	-0.011	0.084	0.448	-0.178	0.153
TREND.ON	ERRORB71	-0.012	0.067	0.432	-0.143	0.119
LOGRT.ON	AGE	-0.559	0.025	<.001	-0.607	-0.508
LOGRT.ON	Inattention	0.290	0.046	<.001	0.200	0.379
LOGRT.ON	Hyp/Imp	-0.062	0.047	0.091	-0.154	0.029
LOGRT.ON	ERRORB71	-0.200	0.035	<.001	-0.268	-0.132

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 36. Standardized values for association between differences in SWAN domains and differences in DSEM parameters for block 7B

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.155	0.081	0.022	-0.322	-0.004
PHI.ON	Inattention	0.139	0.123	0.126	-0.099	0.388
PHI.ON	Hyp/Imp	0.073	0.121	0.267	-0.165	0.312
PHI.ON	ERRORB72	0.189	0.089	0.015	0.019	0.371
LOGV.ON	AGE	-0.392	0.028	<.001	-0.446	-0.337
LOGV.ON	Inattention	0.242	0.045	<.001	0.153	0.328
LOGV.ON	Hyp/Imp	0.034	0.045	0.225	-0.054	0.122
LOGV.ON	ERRORB72	0.155	0.030	<.001	0.097	0.213
TREND.ON	AGE	-0.282	0.087	<.001	-0.451	-0.110
TREND.ON	Inattention	-0.019	0.131	0.442	-0.281	0.237
TREND.ON	Hyp/Imp	0.212	0.135	0.057	-0.053	0.487
TREND.ON	ERRORB72	0.214	0.119	0.042	-0.030	0.431
LOGRT.ON	AGE	-0.534	0.056	<.001	-0.635	-0.415
LOGRT.ON	Inattention	0.355	0.093	<.001	0.169	0.535
LOGRT.ON	Hyp/Imp	-0.193	0.098	0.025	-0.389	0.000
LOGRT.ON	ERRORB72	-0.382	0.085	<.001	-0.543	-0.213

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Supplement I: Association between Age and DSEM parameters

Table 37. Standardized values for association between differences in Age and differences in DSEM parameters for block 1

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.157	0.054	0.002	-0.261	-0.050
LOGV.ON	AGE	-0.155	0.032	<.001	-0.217	-0.092
TREND.ON	AGE	-0.104	0.072	0.078	-0.244	0.038
LOGRT.ON	AGE	-0.479	0.034	<.001	-0.543	-0.409

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 38. Standardized values for association between differences in Age and differences in DSEM parameters for block 2

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	0.037	0.068	0.29	-0.096	0.170
PHI.ON	ERRORB2	0.164	0.072	0.009	0.025	0.307
LOGV.ON	AGE	-0.231	0.030	<.001	-0.290	-0.172
LOGV.ON	ERRORB2	0.415	0.029	<.001	0.357	0.469
TREND.ON	AGE	0.021	0.066	0.374	-0.109	0.152
TREND.ON	ERRORB2	-0.033	0.084	0.348	-0.195	0.138
LOGRT.ON	AGE	-0.598	0.024	<.001	-0.643	-0.550
LOGRT.ON	ERRORB2	-0.437	0.031	<.001	-0.496	-0.376

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 39. Standardized values for association between differences in Age and differences in DSEM parameters for block 3

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	0.029	0.052	0.286	-0.074	0.130
PHI.ON	ERRORB3	0.009	0.052	0.43	-0.093	0.110
LOGV.ON	AGE	-0.329	0.030	<.001	-0.387	-0.270
LOGV.ON	ERRORB3	0.228	0.031	<.001	0.166	0.288
TREND.ON	AGE	-0.150	0.058	0.006	-0.262	-0.034
TREND.ON	ERRORB3	-0.105	0.062	0.047	-0.226	0.018
LOGRT.ON	AGE	-0.571	0.023	<.001	-0.615	-0.526
LOGRT.ON	ERRORB3	-0.399	0.026	<.001	-0.449	-0.347

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 40. Standardized values for association between differences in Age and differences in DSEM parameters for block 4

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.087	0.057	0.066	-0.198	0.026
PHI.ON	ERROR4COM	0.043	0.064	0.254	-0.082	0.168
PHI.ON	ERROR4INC	0.050	0.066	0.222	-0.078	0.180
LOGV.ON	AGE	-0.286	0.031	<.001	-0.345	-0.225
LOGV.ON	ERROR4COM	0.061	0.035	0.042	-0.008	0.129
LOGV.ON	ERROR4INC	0.248	0.034	<.001	0.178	0.314
TREND.ON	AGE	-0.258	0.052	<.001	-0.357	-0.152
TREND.ON	ERROR4COM	-0.071	0.066	0.142	-0.197	0.060
TREND.ON	ERROR4INC	0.529	0.061	<.001	0.406	0.646
LOGRT.ON	AGE	-0.487	0.024	<.001	-0.534	-0.441
LOGRT.ON	ERROR4COM	-0.128	0.029	<.001	-0.185	-0.070
LOGRT.ON	ERROR4INC	-0.531	0.027	<.001	-0.583	-0.477

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 41. Standardized values for association between differences in Age and differences in DSEM parameters for block 7A

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.121	0.083	0.069	-0.286	0.041
PHI.ON	ERRORB71	0.185	0.087	0.014	0.019	0.361
LOGV.ON	AGE	-0.318	0.029	<.001	-0.374	-0.259
LOGV.ON	ERRORB71	0.259	0.030	<.001	0.199	0.316
TREND.ON	AGE	-0.184	0.055	<.001	-0.290	-0.074
TREND.ON	ERRORB71	-0.013	0.066	0.418	-0.142	0.117
LOGRT.ON	AGE	-0.561	0.026	<.001	-0.610	-0.509
LOGRT.ON	ERRORB71	-0.174	0.035	<.001	-0.242	-0.105

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Table 42. Standardized values for association between differences in Age and differences in DSEM parameters for block 7B

Parameter	Covariate	Estimate	Posterior SD	p	2.5 CI	97.5 CI
PHI.ON	AGE	-0.155	0.078	0.021	-0.312	-0.006
PHI.ON	ERRORB72	0.183	0.088	0.018	0.013	0.357
LOGV.ON	AGE	-0.398	0.028	<.001	-0.451	-0.340
LOGV.ON	ERRORB72	0.179	0.030	<.001	0.119	0.237
TREND.ON	AGE	-0.295	0.089	0.001	-0.460	-0.116
TREND.ON	ERRORB72	0.209	0.124	0.051	-0.039	0.434
LOGRT.ON	AGE	-0.532	0.057	<.001	-0.640	-0.415
LOGRT.ON	ERRORB72	-0.345	0.091	<.001	-0.516	-0.162

[a] Note: PHI = inertia, LOGRT = response speed
[b] LOGV = reaction-time variability, TREND = trend

Supplement K: Table of individual differences in change scores

Table 43. Change score variance per block showing individual differences in change scores

Block comparison	Parameter	Estimate	Std.Err	z-value	p	β
B2 vs B3	$\Delta_{variance}$	0.246	0.014	18.079	<.001	1.000
B2 vs B4	$\Delta_{variance}$	0.250	0.014	17.218	<.001	0.997
B2 vs B7A	$\Delta_{variance}$	0.388	0.019	20.321	<.001	1.000
B7A vs B7B	$\Delta_{variance}$	0.372	0.018	21.181	<.001	0.997